A Picture is worth a thousand words
The Role of pictures in second hand marketplaces

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Abstract

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1 Introduction

Second-hand online marketplaces have increase in popularity in the last decade. Such platforms let users buy and sell any kind of objects from books, furniture, electronics, but predominantly clothes. Online second-hand marketplaces like Vinted have grown considerably over the last years. For example, Vinted went from a revenue of \$ 10M in 2017 to almost \$ 600M in 2023

In 2024, the online resale market is flourishing with a variety of platforms catering to different niches and preferences. *Poshmark* stands out with its social networking features, allowing users to follow favorite sellers and engage with a community-oriented marketplace for fashion, accessories, and home decor. *Depop* attracts a younger demographic, blending marketplace functionality with social media elements, making it a hub for trendy and unique fashion items. *Vestiaire Collective* focuses on luxury pre-owned fashion, ensuring authenticity through a meticulous verification process and promoting sustainable fashion practices globally. These platforms provide diverse options for consumers looking to buy or sell second-hand items, each offering unique features tailored to different segments of the market.

Introduce tise as a platoform

Consumer behavior in second-hand markets is influenced by various factors, including perceived value, environmental consciousness, and economic benefits. Henceforth, the consumer base on these platforms is heterogeneous, ranging from those who prioritize sustainability to avid deal hunters. Some companies emphasize their commitment to sustainability, appealing to eco-conscious consumers who seek to reduce waste and support a circular economy. Others focus more on the economic aspect, attracting buyers looking for cost-effective alternatives to new items. This diversity in consumer motivations reflects the broad appeal and varied marketing strategies of second-hand marketplaces.

The role of these platforms is to reduce information asymmetries between users in buying and selling. Most platforms have a reputational system with reviews and ratings (Filippas et al., 2022). Another way to build trust within the community, it is recommended to add a profile picture and a short bio. This personal touch helps other users feel more connected and confident in their interactions.[1].

As (Troncoso and Luo, 2023) analyzed, the use of a profile picture is not straightforward in building trust, with other platform design choices such as reputational systems and product recommendations also playing significant roles. They state that in online labor marketplaces for freelancers, "looking the part" and job fitness are crucial for securing employment.

In online products marketplaces, the context is similar, sharing the profile picture features, but it is very difficult to "look the part" as a seller. Moreover, in this setting, the same reasoning can be applied to every product, since, the best the product is looking, the easiest is to sell. Platforms,in fact, recommend several best practices. Sellers should ensure items are clean and "make them presentable." Using natural lighting for photographs accurately captures the item's true color and details, with multiple angles, including close-ups of unique features or flaws, should be provided. Additionally, they specifically suggest users to model or "try on" the clothing to help potential buyers better understand the fit and appearance. [2].

First, perceptions of product fit may be formed holistically, based on multiple visual cues in the listing photos, many of which could extend beyond basic product information. For example, visual cues such as the cleanliness and presentation of the item can influence perceptions of its quality and de-

[1]Source: Startup on tise.com

[2]Source: tise.com Guidelines

sirability, which may well influence perceptions of fit for specific needs (e.g., formal occasions vs. casual wear). Second, perceptions of product fit could be category-specific, i.e., the same product might be perceived differently depending on the category under consideration. For instance, while a "vintage-looking" item (condition and brand held constant) may be perceived as a high fit for a retro fashion enthusiast, it may be perceived as a low fit for someone seeking modern, contemporary styles.

In addition to this, the product "fit" can be perceived also in relation of the setting its is presented. For example, the product can be displayed in different ways, such as: using store or stock photos, or presenting it in an informal way, for example in room or as well in a scenic way, with a landscape. For clothing, the product can be also show worn or lying on a surface. In figure 6 I show some common product display on the platform.

Our research is motivated by observations indicating that consumers frequently rely on the presentation of products to assess their suitability in second-hand marketplaces. This judgment is influenced by whether the product is displayed in a professional setting, modeled by individuals, or shown in a homemade environment. The way items are photographed, including the use of models and the clarity of images, plays a crucial role in shaping consumer perceptions and their subsequent purchasing decisions.

Research indicates that judgments based on appearance can have significant downstream effects on decision-making (Olivola and Todorov, 2010). In the context of second-hand marketplaces, the presentation of products can similarly influence consumer perceptions and purchasing decisions. For instance, products that are displayed in professional settings, modeled by individuals, or shown in clear, well-lit photographs often attract more buyers. To the best of our knowledge, however, no academic research has yet investigated the potential downstream consequences of appearance-based perceptions on purchasing decisions in online second-hand marketplaces.

In the marketing literature, (Luo et al., 2008) suggested that consumers often use both objective and subjective criteria to evaluate products. Similarly, we explore whether consumers in second-hand marketplaces use both arguably more objective criteria (e.g., product descriptions, seller ratings, and price) and arguably more subjective criteria (e.g., the presentation quality of the product, the setting of the photograph, and the inclusion of models) when deciding what to purchase.

For this reason, the seller must decide on the level of effort to invest when photographing the product for their listing. Options include taking a picture in a real-life setting, ironing the clothing, wearing it, and capturing a well-lit photograph. These decisions significantly impact the product's perceived value and attractiveness to potential buyers.

To understand the impact of the picture in second-hand markets, I perform a large-scale observational study to answer the following research questions:

- How does the setting of a product photo influence consumer purchasing decisions in second-hand marketplaces?

- What impact does the presence of a person in product photos have on the perceived value and attractiveness of the item?
- To what extent does the perceived professionalism of a product photo affect its likelihood of being sold?
- How does the beauty of the product, as captured in photos, affect consumer perceptions and purchasing behavior?
- How do privacy concerns influence seller decisions regarding the inclusion of personal elements in product photos?
- What is the interplay between review systems and the quality of product photos in influencing consumer trust and purchase decisions?

Our study is backed by data from tise.com the largest second-hand marketplace in Norway. We use data on more than 3M product listings, posted between the first of January 2021 and December 2024.

We leverage modern computer vision techniques ti analyze the first picture of every product listing, the one visible on the "explore" page and the profile picture.

Our research makes significant contributions to the understanding of visual presentation in second-hand marketplaces.

Firstly, we extend the literature on the influence of images in online marketplaces (e.g., Pope and Sydnor (2011), Doleac and Stein (2013), Edelman et al. (2017),Ert et al. (2016), Athey et al. (2022),Troncoso and Luo (2023)) by demonstrating that product photos can impact purchasing decisions based on appearance-related perceptions, beyond established factors like product details or seller reputation. To our knowledge, this study is the first empirical investigation showcasing the critical role of product presentation in second-hand online marketplaces.

Secondly, we contribute to the body of work on online marketplace design and reputation systems (e.g., Sun (2012), Tadelis (2016), Watson et al. (2018), Luca (2017)) by exploring the dynamic interaction between image quality and reputational feedback. This study is among the first to reveal how the quality of product photos, combined with reputation systems, influences consumer trust and purchasing behavior.

Thirdly, we build on the work of (Ma et al., 2019) which explores the impact of image quality on purchasing behavior in peer-to-peer marketplaces. Their findings highlight that higher quality images are associated with increased sales and enhanced perceived trustworthiness, although other factors like view count also play a significant role.

2 Related literature

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3 Data

My study use data from tise.com, that is a prominent second-hand fashion platform primarily serving the Nordic region, encompassing countries such as Norway, Sweden, Denmark, and Finland. The platform is designed to facilitate the buying and selling of pre-owned fashion items, integrating various features to enhance user experience and safety. Key functionalities include an integrated payment solution that ensures secure transactions, a robust search system for specific categories and brands, and options for users to earn extra income through reselling.

The app also emphasizes sustainable shopping by encouraging the reuse and recycling of fashion items, thereby contributing to environmental conservation efforts. Users can upload photos of their items, trying to sell them through the platform. Additionally, Tise offers features for browsing the latest fashion trends, which helps users stay updated with current styles while shopping second-hand.

The community aspect of Tise is significant, with millions of active users who interact within the platform, thereby creating a dynamic marketplace environment. This user base not only drives the economic activity on the platform but also fosters a sense of community among second-hand fashion enthusiasts. The platform's design choices, including reputational systems and product presentation, play a crucial role in influencing purchasing decisions and building trust among users.

Specifically, we limit our analysis to adult clothing apparel, excluding categories such as child & baby, interior & furniture, outdoor, art & design, devices & audio, and leisure & hobbies. These excluded categories are retained solely for building metrics related to reputation and user experience on the marketplace.

The primary reasons for choosing Tise over Vinted, the leading second-hand marketplace in Europe, are as follows:

1. Single Market Structure: Unlike Vinted, where users can trade across multiple markets, Tise operates as a single market within each Nordic country. This separation ensures that users within each country interact solely with each other, providing a more localized and cohesive trading experience.

2. Global overview: Tise maintains a comprehensive history of user purchases, allowing for detailed tracking of wardrobes and user experiences. This feature provides valuable data for analyzing consumer behavior and market trends within the platform.

3. Flexibility in Photo Posting: Tise does not prohibit the use of "stock" or professional photos in listings, unlike Vinted. This policy provides a complete overview of posting behavior, offering insights into how different presentation strategies affect consumer engagement and sales.

These factors make Tise a preferable choice for analyzing localized market dynamics, consumer behavior, and the impact of product presentation in second-hand marketplaces.

For each product listing, we scrape all the data available

3.1 Data Collection

Data was collected from tise.com using their hidden API, resulting in approximately 9 Million data points over 4 countries and spanning from January 2016 through March 2024, when the data retrieval was performed.

For a clearer analysis, I decided to subset the data to only the country of Norway. This approach helps to reduce confounding factors such as different legislation, customs, habits, currencies, and behaviors present across the various Nordic countries. Norway is the origin country of Tise and has the highest usage rate of the platform, providing a rich dataset for analysis. Additionally, Norway lacks significant competitors in the second-hand marketplace sector, making it an ideal environment to study the impact of Tise without external market influences.

Subsetting the data to only Norwegian users, the data shrinks to 4.597.382 observations. The data spans across 22 categories.

The observation we use is at product level. Through the API we collect data about the product such as: category, condition, country of origin, reference gender, price, creation date, size, update date, brand, sold status, caption, colors and likes count.

For each user, it was collected the entire wardrobe, with history of sold products, review count, text and average rating.

1. **Number of Listings**
    - **Total Listings**: The total number of items currently listed for sale on the platform.
    - **Category-Specific Listings**: Breakdown of listings by category (e.g., clothing, electronics, furniture).
    - **New Listings per Day**: The average number of new items posted each day.
2. **User Activity**
    - **Total Active Users**: The number of users who have logged in or interacted with the platform in a given period (e.g., daily, weekly, monthly active users).
    - **Average Number of Items Listed per User**: A measure of user engagement, showing how many items a typical user lists.
    - **Repeat Sellers**: Percentage of users who list items multiple times, indicating user retention.
3. **Sales Metrics**

- **Total Sales Volume**: The total number of items sold on the platform over a specific period.
- **Total Revenue Generated**: The total monetary value of all sales made on the platform.
- **Average Sale Price**: The average price of items sold, which can be further broken down by category.
- **Time to Sale**: The average time it takes for an item to sell after being listed.

4. **User Feedback and Reputation**
   - **Average User Rating**: The average rating given to users by buyers, indicating overall satisfaction.
   - **Percentage of Transactions with Feedback**: The proportion of sales that receive feedback, which can indicate user engagement with the reputation system.
   - **Average Number of Ratings per User**: Reflects how often users receive feedback.
5. **Geographical Data**
   - **Distribution of Listings by Region**: How listings are spread across different regions or cities within a country.
   - **Sales by Region**: Regional breakdown of sales volume and revenue.
6. **Platform Growth**
   - **User Growth Rate**: The rate at which new users are joining the platform.
   - **Growth in Listings**: The increase in the number of listings over time, indicating platform expansion.
7. **Sustainability Metrics**
   - **Items Recycled or Reused**: The number of items that were sold or repurposed instead of discarded, contributing to sustainability goals.
   - **Environmental Impact**: Metrics estimating the reduction in carbon footprint or waste due to items being reused rather than bought new.

3.2 Developing variables related to images

1. Profile picture
   (a) Percentage of profile pictures
   (b) gender, age, beauty -¿ how
   (c) faces, logos, avatars
2. Items

3.2.1 Labeling the pictures as Person Self, Homemade Cloth, Professional Model, Professional Cloth

The image analysis was conducted using a model trained with YOLOv8 by Ultralytics. Initially, the YOLOv8 large classification weights, pre-trained on a broad dataset, were fine-tuned to develop a custom model. The model achieved an 89% success rate in out-of-sample validation.

Given the impracticality of manually analyzing all images, a semi-supervised learning approach was employed. First, a training set was created for the "tops" category, starting with 500 training images, and 100 validation images. This process was iterated six times, ultimately expanding the dataset to 1,600 training images and 500 validation images. The lower bound for validation images resulted from the underrepresentation of the "Professional Clothing" category.

In this approach, the initially trained model was used to label additional images. These automatically labeled images were then manually reviewed, and the corrected labels were used to retrain and improve the model further.

The refined model was subsequently applied to categorize images for "Jumpsuits," "Skirts," and "Pants." These categories were selected to represent the "top," "full-body," and "bottom" segments of clothing, respectively.

The last step involved training the classifier using the pre-trained YOLOv8 large model, fine-tuned over 100 epochs. We utilized 62,5% of the 3.200 labeled images for training and 37,5% for validation. The YOLOv8 model, already equipped with robust transfer learning Hartmann et al. (2021), Zhang et al. (2021), and Zhang and Luo (2022), data augmentation (Krizhevsky et al., 2012), and regularization (Srivastava et al., 2014)techniques, effectively mitigates overfitting without requiring additional manual intervention. This streamlined approach allowed us to achieve high performance with minimal adjustments to the standard training process. Once classified, a dummy variable was generated according to the type of subject in the picture.

To create the control variables, I utilized a combination of open-source models. The presence of a person in the image was detected using the MiVOLO model (Kuprashevich and Tolstykh, 2023), which also provided estimates for the person's age. For assessing beauty, I employed the CLIP[3] model, applying it to image crops generated by MiVOLO. Image quality measures, such as resolution and the detection of duplicate images, were calculated using the CleanVision library[4]. This tool also identified whether images were too dark or too light, contributing to the overall quality assessment.

For the clothing-specific variables, the CLIP model was again used to determine whether the garment appeared ironed and to evaluate the environment

[3]CLIP (Contrastive Language-Image Pretraining), is a neural network model developed by OpenAI that can understand and associate images with textual descriptions. It works by training on a large dataset of images and their corresponding text, learning to align visual and textual information. CLIP can be used for various tasks, such as image classification, zero-shot learning, and content-based image retrieval, by evaluating how well an image matches a given text prompt. Its versatility and ability to generalize across different tasks make it a powerful tool in the field of multimodal AI.

[4]`https://github.com/cleanlab/cleanvision`

in which the clothing was presented—whether it was a fancy or messy setting. The vibrancy of the garment colors was also assessed using CLIP. Additionally, dummy variables were created to indicate whether a face was present in the image, whether the subject appeared to be with a boyfriend or girlfriend, and to measure the relative size of the face or body within the image.

In our analysis, CLIP was employed to quantitatively assess the neatness of an image's background. This approach leverages the model's ability to understand and compare complex visual and textual concepts. Specifically, we evaluated each image against a set of positive descriptors (e.g., "a neat and clean background") and negative descriptors (e.g., "a messy background"). By calculating the similarity between the image and these descriptors, we derived a neatness score, which serves as a robust metric for background quality. This automated method provides a consistent and objective measure that can be crucial in evaluating the presentation quality of products in online marketplaces. Such a metric is particularly valuable in marketing and economics research, where visual presentation can significantly influence consumer behavior and purchasing decisions.

Humans are inherently visual creatures, making the visual presentation of products crucial in online marketplaces. Previous research has shown that visual appeal significantly influences consumer behavior and decision-making in online environments (Belém et al., 2019). The design of these platforms often reinforces this tendency by incentivizing users to post images that include themselves, mirroring the practices of influencers. Studies have demonstrated that consumers are more likely to trust and engage with sellers who use personal photos, as this aligns with social media trends where personal branding and visual storytelling are key to engagement (Athey et al., 2022). By encouraging users to emulate influencers, the platform taps into established consumer behavior patterns, where the visual appeal of a product, coupled with the perceived authenticity of the seller, can significantly drive purchasing decisions (Ma et al., 2019). This interplay between human visual preferences and platform design choices underscores the importance of image quality and presentation in shaping consumer behavior.

4 Data Analysis

4.1 How does people presence affect posting behavior?

$$
\begin{aligned}
p_{i,j} = \alpha_i &+ \beta_0 \cdot \text{ProductPicture} + \beta_1 \cdot \text{ProfilePicture}_j \\
&+ \beta_2 \cdot \text{Reputation} + \beta_3 \cdot \text{Experience}_t \qquad (1)\\
&+ \beta_4 \cdot \chi_{i,j} + \epsilon_{i,j,t} \qquad (2)
\end{aligned}
$$

- $p_{i,j}$: Predicted price for product i and individual j.
- α_i: The intercept term specific to product i, capturing product-specific effects.

- ProductPicture_i: Set of variables representing the visual aspects of the product image, including whether a product picture is present, if the seller is present in the image, and the aesthetic quality or beauty of the image.
- ProfilePicture_j: Set of variables capturing details about the individual's profile picture, including whether a profile picture exists, if the individual is present in the picture, and the perceived attractiveness of the individual in the image.
- Reputation_j: Set of variables reflecting the individual's reputation, measured by the number of reviews and the overall score or rating they have received.
- $\text{Experience}_{j,t}$: This variable accounts for the individual's experience, indicated by the number of products they have posted and sold at given time t (including those not reviewed).
- $\chi_{i,j}$: A set of controls representing other factors such as the bio of the seller and the description of the product, the category of the product, and brand.
- $\epsilon_{i,j,t}$: The error term capturing unexplained variability in the dependent variable for product i and individual j at time t.

4.2 How does people presence affect purchasing choices?

In addition to predicting price, we can use a logit model to examine the likelihood of a product being sold or remaining unsold. This model will include the same predictors as the linear regression, with the addition of price as a control variable:

$$\begin{aligned}\text{logit}(SaleOutcome_{i,j}) = \alpha_i &+ \beta_0 \cdot \text{ProductPicture} + \beta_1 \cdot \text{ProfilePicture}_j \\ &+ \beta_2 \cdot \text{Reputation}_j + \beta_3 \cdot \text{Experience}_t \quad (3)\\ &+ \beta_4 \cdot \chi_{i,j} + \beta_5 \cdot \text{Price}_{i,j} + \epsilon_{i,j,t} \quad (4)\end{aligned}$$

Where:

- $\text{SaleOutcome}_{i,j}$ is a binary variable indicating whether the product i was sold (1) or remained unsold (0).
- $\text{Price}_{i,j}$ is the control variable representing the price of the product i.

For products that are sold, a linear regression model can be used to predict the time it takes to sell the product, considering the same factors:

$$\begin{aligned}\text{TimeToSell}_{i,j} = \alpha_i &+ \beta_0 \cdot \text{ProductPicture} + \beta_1 \cdot \text{ProfilePicture}_j \\ &+ \beta_2 \cdot \text{Reputation}_j + \beta_3 \cdot \text{Experience}_t \quad (5)\\ &+ \beta_4 \cdot \chi_{i,j} + \beta_5 \cdot \text{Price}_{i,j} + \epsilon_{i,j,t} \quad (6)\end{aligned}$$

Where:

- $\text{TimeToSell}_{i,j}$ represents the time it took to sell product i by individual j, for those products that were sold.
- $\text{Price}_{i,j}$ controls for the effect of the price on the time to sell.

5 Results

The results of the study are presented in this section. The key findings are summarized in the table and figure below.

	coef	**std err**	**z**	**P> |z|**	**[0.025**
Intercept	3.4017	0.010	330.195	0.000	3.381
condition[T.new]	0.0662	0.007	10.075	0.000	0.053
condition[T.no_condition]	0.1552	0.010	15.782	0.000	0.136
condition[T.used]	-0.2294	0.013	-17.448	0.000	-0.255
condition[T.well_used]	-0.5620	0.059	-9.605	0.000	-0.677
C(sizeNumeric, Treatment(reference=3))[T.0]	-0.3153	0.021	-14.858	0.000	-0.357
C(sizeNumeric, Treatment(reference=3))[T.1]	-0.1011	0.008	-12.856	0.000	-0.116
C(sizeNumeric, Treatment(reference=3))[T.2]	-0.0084	0.007	-1.235	0.217	-0.022
C(sizeNumeric, Treatment(reference=3))[T.4]	-0.0782	0.010	-7.521	0.000	-0.099
C(sizeNumeric, Treatment(reference=3))[T.5]	-0.1472	0.018	-8.385	0.000	-0.182
C(sizeNumeric, Treatment(reference=3))[T.6]	-0.1194	0.035	-3.395	0.001	-0.188
C(sizeNumeric, Treatment(reference=3))[T.7]	-0.1904	0.082	-2.326	0.020	-0.351
C(sizeNumeric, Treatment(reference=3))[T.8]	-0.1948	0.090	-2.158	0.031	-0.372
C(title_length_category)[T.Short]	1.0052	0.005	206.660	0.000	0.996
C(title_length_category)[T.Medium]	1.1618	0.004	272.742	0.000	1.153
C(title_length_category)[T.Long]	1.2347	0.005	247.289	0.000	1.225
C(caption_length_category)[T.Short]	0.1276	0.011	12.131	0.000	0.107
C(caption_length_category)[T.Medium]	0.2574	0.012	22.237	0.000	0.235
C(caption_length_category)[T.Long]	0.3555	0.014	26.242	0.000	0.329
is_low_information_issue[T.True]	-0.1833	0.264	-0.694	0.488	-0.701
is_light_issue[T.True]	-0.6132	0.646	-0.949	0.343	-1.880
is_dark_issue[T.True]	-0.3161	0.256	-1.234	0.217	-0.818
is_blurry_issue[T.True]	-0.2248	0.098	-2.302	0.021	-0.416
is_exact_duplicates_issue[T.True]	-0.0248	0.051	-0.483	0.629	-0.125
is_near_duplicates_issue[T.True]	-0.0136	0.014	-1.004	0.315	-0.040
cumulative_avg	0.0264	0.002	17.077	0.000	0.023
review_count	0.0004	0.000	2.500	0.012	7.86e-05
cumulative_sold	-0.0004	0.000	-3.141	0.002	-0.001
cumulative_posts	0.0005	3.28e-05	15.180	0.000	0.000
cloth_self	-0.2716	0.007	-36.919	0.000	-0.286
person_professional	0.1435	0.008	18.787	0.000	0.129
person_self	-0.0300	0.008	-3.649	0.000	-0.046

6 Conclusion

This is the conclusion of the study. The findings suggest that further research is needed to fully understand the implications of the results.

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Appendix

Informal setting without person

Pro-like setting without person

Informal setting with person

Professional setting with person

Figure 1: Examples of product display

	Dependent variable: np.log(price)						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cloth Professional	0.585***	0.571***	0.571***	0.484***	0.485***	0.417***	0.425***
	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)
Person Professional	0.716***	0.698***	0.695***	0.603***	0.604***	0.517***	0.530***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Person Self	0.435***	0.431***	0.428***	0.360***	0.360***	0.277***	0.292***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Condition		✓	✓	✓	✓	✓	✓
Sizes			✓	✓	✓	✓	✓
Text				✓	✓	✓	✓
Experience					✓	✓	✓
Reviews						✓	✓
Profile Picture							✓
Observations	125395	125395	125395	125395	125395	125395	125395
R^2	0.101	0.105	0.106	0.157	0.157	0.213	0.218
Adjusted R^2	0.093	0.097	0.098	0.150	0.150	0.206	0.211

Table 1: Price Comparison

	Dependent variable: sold						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cloth Professional	0.511***	0.516***	0.549***	0.514***	0.488***	0.478***	0.488***
	(0.027)	(0.027)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Person Professional	0.690***	0.698***	0.758***	0.725***	0.690***	0.676***	0.688***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)
Person Self	0.275***	0.275***	0.363***	0.338***	0.326***	0.312***	0.324***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)
price_quintile	0.148***	0.149***	0.153***	0.129***	0.133***	0.126***	0.124***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Condition		✓	✓	✓	✓	✓	✓
Sizes			✓	✓	✓	✓	✓
Text				✓	✓	✓	✓
Experience					✓	✓	✓
Reviews						✓	✓
Profile Picture							✓
Observations	125395	125395	125395	125395	125395	125395	125395
Pseudo R^2	0.027	0.027	0.036	0.040	0.056	0.057	0.058

Table 2: Price Comparison

	Dependent variable: np.log(TimeToSell)						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cloth Professional	-0.112*	-0.122*	-0.137**	-0.127*	-0.124*	-0.161**	-0.153**
	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)
Person Professional	-0.202***	-0.213***	-0.237***	-0.227***	-0.234***	-0.280***	-0.260***
	(0.039)	(0.040)	(0.040)	(0.040)	(0.040)	(0.039)	(0.040)
Person Self	-0.094**	-0.095**	-0.135***	-0.131***	-0.128***	-0.232***	-0.210***
	(0.038)	(0.038)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
price_quintile	-0.138***	-0.140***	-0.144***	-0.137***	-0.126***	-0.191***	-0.193***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Condition		✓	✓	✓	✓	✓	✓
Sizes			✓	✓	✓	✓	✓
Text				✓	✓	✓	✓
Experience					✓	✓	✓
Reviews						✓	✓
Profile Picture							✓
Observations	40705	40705	40705	40705	40705	40705	40705
R^2	0.006	0.007	0.008	0.009	0.022	0.033	0.034
Adjusted R^2	-0.016	-0.016	-0.014	-0.013	-0.000	0.011	0.012

Table 3: Price Comparison