Price determinants for remanufactured electronic products: a case study of eBay UK

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Abstract

In this paper we analyse the market determinants of price differentials between new and remanufactured products in Electronics by using data on purchases made on eBay UK. The empirical analysis is carried out by means of linear regression methods, which are capable of controlling for the presence of collinearity among the explanatory variables. Our empirical results suggest that seller reputation, length of warranties, proxies of demand and supply of remanufactured products, duration and end day of product listings as well as the availability of return policies are important determinants of price differentials. Most importantly, we find that the seller identity plays an important role, as our empirical results are predominantly driven by transactions carried out by non manufacturer-approved vendors.

Key words

Remanufacturing, Price differentials, Regression methods, Collinearity, Bootstrapping.

1. Introduction

Remanufacturing can be defined as “returning a used product to at least its original performance with a warranty that is equivalent to or better than that of the newly manufactured product” (British Standards, BS8887: Part 2 2009). This implies that remanufactured products are allegedly, in terms of product performance, identical to their corresponding new products. Through a stringent remanufacturing process, used products are disassembled, serviced, tested and their components are repaired, replaced or processed to attain like-new condition.

In a market environment, the remanufacturing process can be carried out by Original Equipment Manufacturers (OEMs), manufacturer-approved and non manufacturer-approved vendors. The potential benefits of remanufacturing are twofold. First, it extends the useful life of a product, thus reducing the demand for new products and environmental burden (U.S. EPA 1997, 1998, 2011). Second, it can potentially be a profitable economic activity for OEMs, given the residual value inherent in the used products and the cost savings from remanufacturing. According to Lund (1996), the size and scope of U.S. remanufacturing operations accounts for total sales in excess of $53 billion per year with 73,000 companies across over 46 major product categories and 480,000 employees. In the 2004 survey “Remanufacturing in the UK: a significant contributor to sustainable development?” it was estimated that remanufacturing and reuse contributed £5 billion per annum to the UK economy (Parker 2004). This survey also found that each year the UK remanufacturing industry saves 270,000 tonnes of materials (mostly metals) from recycling or scrapping, and employs at least 500,000 people (Parker 2004).

Despite the potential benefits of remanufacturing, the current literature suggests that research has barely begun to investigate market-related issues in the area of Closed-Loop Supply Chains (CLSCs) as a whole. Prior production research literature has studied various strategic and tactical issues arising in remanufacturing systems (e.g. Corbett & Kleindorfer 2001a, 2001b, Tang, Grubbström & Zanoni 2004, Nakashima, et al. 2004, Guide & Van Wassenhove 2006a, 2006b, Kleindorfer et al.

2005, Grubbström & Tang 2006, Ahn, Lee & Kim 2011). This stream of literature tends to be analytical in nature. The need for empirical research to quantify the parameters used in analytical models is essential. Measures (e.g. price determinants) to extend the economic lives of electronic products are receiving increased attention in the field of remanufacturing strategy. However, we have found that the investigation of market-related measures is rather limited in the existing production research literature. In their recent reviews, Guide & Van Wassenhove (2006a, 2009), and Atasu et al. (2008) stressed the need for research exploring empirical studies of market factors in CLSCs. Despite the well-designed operational system, a lack of understanding of prices and markets poses barriers to the development of the remanufacturing industry (Guide & Van Wassenhove 2009, p.16). Guide & Van Wassenhove (2009) stress the opportunity for such work to lead industry practice since industry has long operated on the basis of common wisdom rather than systematic empirical studies.

Some recent empirical studies on market factors in CLSCs are available. Guide & Li (2010) studied cannibalisation based on online auctions for a consumer product and a commercial product to determine consumers' willingness to pay for both new and remanufactured products. Ovchinnikov (2011) has studied the pricing and remanufacturing strategy of a firm that offers both new and remanufactured versions of its products. A model of demand cannibalisation and a behavioural study that estimates the fraction of consumers who switch from a new to remanufactured product are presented. More recently, Agrawal, Atasu & Ittersum (2012) have investigated how the presence of remanufactured products and the identity of the remanufacturer influence the perceived value of new products. Through behavioural laboratory experiments, in the absence of a third-party remanufacturer the authors found that the presence of products remanufactured and sold by OEMs reduces the perceived value of new products. Subramanian & Subramanyam (2012) have studied market factors, and report that seller reputation significantly explains the price differentials between new and remanufactured products. Remanufactured products listed by OEMs or their authorised factories are sold at relatively higher prices. In the presence of seller reputation and remanufacturer identity, the authors find that stronger warranties are not significantly associated with higher prices paid for remanufactured products.

In this paper, we study the market determinants of price differentials between new and remanufactured products by using data on purchases made on eBay UK. We consider the Electronics product category, where remanufacturing activities are significant and a sufficient number of transactions for both new and corresponding remanufactured products can be found. We carry out the empirical analysis by means of three linear regression methods: the standard Ordinary Least Square Regression (OLSR), Ridge Regression (RR) and Mixed Regression (MR). By applying these methods, we are able to control for the presence of collinearity among the explanatory variables considered in our dataset. Our empirical results suggest that the reputation of vendors, the length of warranties provided for remanufactured products, the proxies of demand and supply of the same remanufactured items, the lengths of advertisement, the ending time of remanufactured product listings as well as the availability of return policies are important determinants of price differentials.

This study contributes to the remanufacturing industry of Electronics, and provides insights into the price determinants for sellers with different identities. We find that the seller identity (manufacturer-approved versus non manufacturer-approved) is an important market determinant of price differentials. In fact, our empirical results are predominantly driven by transactions carried out by non manufacturer-approved vendors. In order to compete in the online trading of remanufactured electronic products, non manufacturer-approved sellers are urged to advance their online market performance. We conclude that the price differentials of remanufactured products listed by manufacturer-approved sellers are driven by a different set of market determinants that are not available on the eBay market dataset, yet require further research attention.

The potential for cannibalisation of new product sales by remanufactured versions of the same product is a central issue in the continuing development of CLSCs (Guide & Li (2010). This is due to the fact that remanufactured products have the same functionality as new products. Therefore, as suggested by Buday (1989) and Mason & Milne (1994), remanufactured products are likely to incur a significant risk of cannibalisation of new product sales. In our study, we do not intend to address the cannibalisation issue as our dataset does not capture the essential information to understand the potential impact of offering new and remanufactured products at the same time. However, the research on the potential for cannibalisation of new product sales by remanufactured goods is interesting and deserves further attention.

The remainder of the paper is organised as follows. Section 2 discusses a number of market determinants of price differentials between new and remanufactured products. Section 3 describes our datasets and Section 4 sets out the variables considered in our empirical analysis. Section 5 reports the results from our preliminary analysis. Section 6 introduces the empirical model and the methodologies used. Section 7 sets out the empirical results together with a number of robustness checks. Section 8 concludes the paper.

2. Market Determinants of Price Differentials between New and Remanufactured Products

2.1. Seller Reputation

In the literature, there are mixed findings for the effect of seller reputation on prices paid for used products (Houser & Wooders 2006, Lucking-Reiley et al 2007, Bajari & Hortaçsu 2003, Livingston 2005, Eaton 2007, Melnick & Alm 2002). In other words, negative (positive) reputation can either have a negative (positive) effect or no impact on used product prices. Although remanufactured products differ significantly from used products, the aforementioned literature suggests that seller reputation would significantly explain price differentials between new and remanufactured products. A seller's reputation can be measured along two dimensions: positive and negative (see Resnick et al. 2006 for a review). On eBay, buyers can provide positive, neutral or negative feedback. The counts of each type of feedback together with textual comments for the past 12 months are reported. The literature (Houser & Wooders 2006, Lucking-Reiley et al. 2007, Standifird 2001) suggests that the feedback counts can be used as appropriate measures for seller reputation. Thus, we consider the number of positive feedback counts as a measure of seller positive reputation. On the one hand, Cabral & Hortaçsu (2010) and Resnick & Zeckhauser (2002) show that market participants perceive neutral feedback negatively. Thus, we combine the total number of neutral and negative feedback counts as a measure of seller negative reputation. Subramanian & Subramanyam (2012) report that positive (negative) seller reputation for remanufactured products is negatively (positively) associated with price differentials. We expect that greater positive seller reputation is associated with lower price differentials, while greater negative seller reputation is associated with higher price differentials.

2.2. Seller Identity

Within the Electronics category, there are two types of sellers listing remanufactured products: the manufacturer-approved vendors and non manufacturer-approved sellers. These latter sellers professionally restore items to working order, but are not approved by the OEMs. According to eBay UK, regardless of the seller identity, all listed remanufactured products have been inspected, cleaned, and repaired to full working order and are in excellent condition. In the literature, very little has been done to examine the consumer preference and the price difference for items sold by manufacturer-approved and non manufacturer-approved sellers. Ferrer & Swaminathan (2006) assume in their analytical model that consumers have a higher preference for remanufactured products offered by manufacturer-approved vendors, whereas in Ferguson & Toktay (2006) consumers do not differentiate between remanufactured products offered by either manufacturer-approved or unauthorised vendors. However, a buyer may be concerned about the remanufacturing process due to the process complexity, technical expertise, equipment and capital investment. Subramanian & Subramanyam (2012) find that products remanufactured by authorised factories are purchased at relatively higher prices than products remanufactured by unauthorised third parties. We expect that products remanufactured by manufacturer-approved vendors are associated with lower price differentials.

2.3. Remanufactured Product Warranty

Product warranty is an important element, especially when consumers consider purchasing a remanufactured product as a substitute for the corresponding new product. Recently, the study of Ovchinnikov (2011) found that both quality-conscious (high-end) and price-sensitive (low-end) respondents were more open to considering a remanufactured product backed by a strong warranty, in particular if this warranty came directly from a manufacturer they know and trust. The analysis of Subramanian & Subramanyam (2012) shows that, in the presence of seller reputation and remanufacturer identity, stronger warranties are not significantly associated with higher prices paid for remanufactured products. We expect that longer (i.e. stronger) warranties are associated with higher price differentials.

2.4. Demand and Supply Proxies

For manufacturer-approved and non manufacturer-approved sellers, there are questions about the demand for both new and corresponding remanufactured products. Athey & Haile (2002) show that in certain auctions, demand can be identified from observing the price and the number of bidders. In eBay, it is possible to obtain the information about the number of bidders as well as the number of hit counts (the number of times an item has been viewed by potential buyers). Having a good understanding of demand for remanufactured products enables producers to set either the reserve or buy-it-now prices, and it helps identify what remanufactured products are in demand. Subramanian & Subramanyam (2012) find that a greater quantity of remanufactured products available from the seller is associated with a lower price differential, and the proxy for product demand is negatively associated with price differential. Based on these findings, Subramanian & Subramanyam (2012) suggest that buyers may perceive a greater quantity available for a remanufactured product as evidence of a well-established seller, and more popular remanufactured products should be discounted less. We expect that higher demand proxy is associated with lower price differentials, whereas larger quantities available from sellers are associated with higher price differentials.

3. Data

EBay offers a rich set of Application Programme Interfaces (APIs) that allows third party vendors to access eBay data and information. The APIs are accessed via writing custom software scripts that retrieve information from the online auction site. The scripts are written in PHP (Hypertext Preprocessor), a popular server-scripting language, while data downloaded is saved in an SQL database, making it possible to search and export data easily. The methodology adopted involves three main steps. First, we compile all available eBay Electronics subcategories. Next, the application uses eBay's APIs to retrieve listings of products for each subcategory. Although it is possible to impose filters on the list, we do not apply them as we intend to select products randomly within these subcategories. Second, our software iterates around the product listings and downloads all the available information provided by eBay. In the final step, an export routine outputs the required data in a specified format.

In this study, we have only considered the product category of Electronics sold on eBay UK for three reasons. Firstly, within this category the number of remanufacturing activities is significantly higher than in any other eBay UK categories. Secondly, electronics was the only product category in which we were able to find a sufficient number of transactions for both new and corresponding remanufactured products. Finally, methodologically, electronic products (and their titles) tend to be standardised, making it easier to identify products of the same model.

From 18 May to 9 June 2012, we collected a rich transaction-level dataset on new and corresponding remanufactured products sold under the eBay UK product category of Electronics, across all listing types (both fixed and non-fixed price listings). The dataset consists of 352 Electronics product titles. Under each title, there are transactions for both new and corresponding remanufactured products. We ensure both new and corresponding remanufactured products are exact matches (e.g. same product specification: model and version). To compute price differentials (see Section 4), we ensure that each of the 352 product titles has at least one new product transaction and at least one corresponding remanufactured product transaction. Under 352 product titles, there are 1260 new product transactions and 917 corresponding remanufactured product transactions. Thus, our resulting dataset includes a total of 917 transactions, for which we can extract observations for price differentials and related determinants, such as the counts of seller positive and negative feedback, the length of seller incumbency, the length of warranty offered, proxies for the quantities of products supplied by eBay sellers and demanded by eBay buyers, the seller identity (manufacturer-approved and non manufacturer-approved vendors), the length of listing and listing end time/day, and the availability of return policies. Across our dataset, we ensure no identical sellers, i.e. no sellers who list multiple adverts for the same remanufactured product.

We then partition our dataset into two subsamples. The first encompasses the Electronics products remanufactured by manufacturer-approved vendors and consists of 481 transactions. The second contains the products remanufactured by non manufacturer-approved sellers and consists of 436 transactions. Our aim is to investigate whether the pattern of results obtained for the entire dataset still holds when the two partitioned datasets are taken into consideration. Section 7 discusses these results and insights in more detail.

4. Variables

4.1 Dependent Variable: Price Differentials

We denote the price differential of a remanufactured product transaction as PD_i. We compute the price differentials PD_i, $i = \{1, 2, \ldots, 917\}$ as the difference between the average price of a new product and the price of the corresponding remanufactured product, as a fraction of the average price of the new product, according to the formula below:

$$PD_i = \frac{Average\ Price_{New} - Price_{Remanuf,\, i}}{Average\ Price_{New}} \times 100\% \qquad (1)$$

Here, the price of new and corresponding remanufactured products is referred to as the sold price plus the postage charge minus selling fees (including insertion fee and final value fee).

In our dataset the above ratio takes mainly positive values with an upper bound at 1. However, for some specific transactions the ratio assumes negative values. Negative values are possible because there may be certain seller- or transaction-related dimensions (such as seller reputation) that may lead a remanufactured product to be purchased at a higher price than a corresponding new product. In the next Section we discuss the set of explanatory variables that we believe are good candidates to explain the variability of price differentials.

4.2 Explanatory Variables and Hypotheses

Seller reputation: For each transaction *i*, we use the number of positive feedback counts ($POSREP_i$) as a measure of seller positive reputation, and the number of negative plus neutral feedback counts ($NEGREP_i$) as a measure of seller negative reputation. These two measures enable us to test for the following null hypotheses:

Hypothesis H_{1a}: Greater positive seller reputation is associated with lower price differentials.

Hypothesis H_{1b}: Greater negative seller reputation is associated with higher price differentials.

Length of seller incumbency: We account for the potential effect of a seller's length of incumbency in eBay on the perceived reputation by customers and, hence, on the perceived values of remanufactured products by including $INCUMB_i$ as an explanatory variable. The length of seller's incumbency is measured as the number of days elapsed from the registration with eBay of sellers to the first day of listing products. This makes it possible to test for the following null:

Hypothesis H_2: Longer sellers' incumbency is associated with lower price differentials.

Length of warranty: The duration of warranty could affect the purchasing price of a remanufactured product. We control for this effect by including the variable $WARR_i$, which captures the length of the warranty in months for each remanufactured product transaction. The null that we test is the following:

Hypothesis H_3: Longer warranties are associated with lower price differentials.

Demand and supply proxies: We expect demand and supply factors to exert, respectively, a negative and positive impact on price differentials. We consider the number of hit counts plus the number of bid counts placed for each remanufactured product transaction as a proxy of demand factors (DEM_i), whereas the available quantity of the remanufactured product is used as a proxy of supply factors (SUP_i). In this case the nulls that we test are the following:

Hypothesis H_4: Higher demand proxy is associated with lower price differentials.

Hypothesis H_5: Larger quantities available from sellers are associated with higher price differentials.

Seller identity: We assign $MANUF_i$ a value of 1 if the remanufactured product transaction is carried out by a manufacturer-approved vendor, and 0 otherwise, so that we can test the following null:

Hypothesis H_6: Products remanufactured by manufacturer-approved vendors are associated with lower price differentials.

Duration: The length of advertisement of listed products might have an impact on the price paid for a remanufactured product. A possible reason is that longer availability of a product on eBay enables a more careful assessment by potential buyers. Accordingly, we control for this pattern by including the explanatory variable $DURAT_i$, which measures the number of days elapsed since a certain remanufactured product is first listed. The null that we test in this case is the following:

Hypothesis H_7: Longer listing durations are associated with lower price differentials.

Listing end time/day: Prior research has discussed the possibility that the ending time of an eBay listing may be associated with the price paid (Lucking-Reiley et al. 2007, Simonsohn 2010). One reason is the potentially closer attention paid by buyers during weekends or night time (non-working) hours. Accordingly, we control for these patterns by considering two dummy indicators: $WKND_i$, which captures whether the listing end time for a remanufactured product transaction was at weekends (Saturday or Sunday), and $NIGHT_i$, which captures whether the listing end time for the same transaction was during night hours (from 6pm to 6am). We assign $WKND_i$ the value of 1 if the ending time of a remanufactured product transaction is at weekends, and 0 otherwise. We assign $NIGHT_i$ the value of 1 if the ending time is between 6pm and 6am, and 0 otherwise. Thus, the following two nulls are tested:

Hypothesis H_{8a}: Remanufactured product listings which end at weekends are associated with lower price differentials.

Hypothesis H_{8b}: Remanufactured product listings which end during night hours are associated with lower price differentials.

Return Policy: We assign $RETURN_i$ the value of 1 if a remanufactured product can be accepted for return by vendors, and 0 otherwise. In this case, the null under scrutiny is the following:

Hypothesis H_9: Remanufactured products with a return policy are associated with lower price differentials.

5. Preliminary Analysis

We start our analysis by carrying out some preliminary statistics. The upper panel of Table 1 reports the basic statistics for the eleven candidate explanatory variables used in the regression analysis whereas the lower panel sets out the pair wise correlation indices together with the relative eigenvalues. These values suggest that the explanatory variables are loosely correlated, with the only exception being $POSREP_i$ and $NEGREP_{i,}$ for which the correlation index is 0.946. (The partial correlation index between these two variables calculates to 0.957.) Such a result is also supported by the eigenvalues of the design matrix. If all the independent variables in the dataset were uncorrelated, all the eleven eigenvalues would be equal to unity. The greater the pair wise correlations, the wider the eigenvalue spectrum. In Table 1, the first ten eigenvalues account for approximately 99 percent of the total, so that almost all of the variation in the eleven independent variables can be represented in ten dimensions only. These figures suggest that collinearity might plague empirical estimates obtained by applying standard OLSR. In Section 6, we present a brief outline of Ridge Regression (RR) and Mixed Regression (MR) methods as statistical tools which can be used to mitigate the issue of collinearity.

Insert Table 1 about here

The upper panel of Table 2 shows that the mean of price differentials (0.100) as defined in Eq. (1) is positive and statistically different from 0. However, the large standard deviation (0.281) suggests that it is not rare to have negative differentials for specific products. In fact, about 10 percent of observations in our dataset present negative price differentials. We then compute the mean and standard deviation of the price differentials for the two partitioned datasets previously defined. These results are similar to the mean and standard deviation for the full dataset.

Insert Table 2 about here

In Fig. 1, we plot the kernel probability distribution of price differentials for the two partitioned datasets. The two kernel distributions are characterised by similar means but different shapes. Statistical tests for equality in mean, median, variance and distributions are then used to investigate whether the price differentials between the two partitioned datasets are indeed different. The results reported in the lower panel of Table 2 suggest that the null of equality in median (Mann-Whitney test), variance

(Levene test) and distributions (Barnett-Eisen and Kolmogorov-Smirnov tests) are soundly rejected at standard significance levels. Similarly, the Chow test soundly rejects the null of equality between linear regressions fitted to the two partitioned subsamples. Ghilagaber (2004) shows the Chow test presents good size and power as long as the sample sizes are similar and homoschedasticity is moderate. We note that the White tests reported in Tables from 3 to 5 actually suggest weak forms of homoschedasticity. All in all, the above results suggest that price differentials for items sold by manufacturer-approved and non manufacturer-approved vendors present different stochastic properties.

Insert Fig. 1 about here

6. Empirical Model and Methodology

In line with previous studies, we allow for the possibility that the relationship between price differentials and their determinants set out in Section 4 is nonlinear by using a log-log transformation of both the dependent and explanatory variables. For instance, as highlighted by Subramanian & Subramanyam (2012), it seems reasonable to expect that higher levels of positive (negative) seller reputation are associated with lower (higher) price differentials with a diminishing effect. Therefore, we consider the following model specification:

$$\begin{aligned} -\ln(1-PD_i) &= \alpha_1 + \alpha_2 \ln(POSREP_i) + \alpha_3 \ln(NEGREP_i) + \alpha_4 \ln(INCUMB_i) + \\ &+ \alpha_5 (WARR_i) + \alpha_6 \ln(DEM_i) + \alpha_7 \ln(SUP_i) + \alpha_8 (MANUF_i) + \alpha_9 (WKND_i) + \\ &+ \alpha_{10} (NIGHT_i) + \alpha_{11} (DURAT_i) + \alpha_{12} (RETURN_i) + \varepsilon_i \quad (i = 1,..,917) \end{aligned} \tag{2}$$

The above log-log specification has two desirable features. First, the transformation of the dependent variable is directionally consistent with price differentials. Second, the slope coefficients in Eq. (2) can be interpreted as elasticities. We carry out empirical estimations of Eq. (2) by using standard heteroschedasticity consistent (Eicher-White) OLSR estimators. However, as highlighted in Section 5, the presence of collinearity among explanatory variables is a statistical issue that potentially impairs OLSR empirical estimates. Multicollinearity, by inflating the standard errors of parameter estimates, might reduce the statistical and economic significance of our results. For this reason, we correct the undesirable effects of multicollinearity by re-estimating our log-log regression using a Ridge Regression (RR) method. In contrast to the standard OLSR estimators, RR methods add a constant *k* to each diagonal element of the cross-product matrix of the explanatory variables before it is inverted (see Hoerl, Kennard & Baldwin 1975). While this introduces bias into the coefficient estimates, the inflated variances are simultaneously reduced. Extensive Monte Carlo simulation experiments support the use of RR when the independent variables are highly correlated, and several successful applications of ridge analysis have been reported (see Annaert et al 2013). We then carry out empirical estimates of Eq. (2) by using a third method based on Theil's (1971) Mixed Regression (MR). The mixed estimation technique is a method of combining sample data with prior linear stochastic constraints on the parameters of the model. Its principal advantages over standard OLSR are that, under appropriate circumstances, MR estimators are superior in Mean Squared Error and it is a valid method for mitigating the effects of multicollinearity (see Belsey, Kuh & Welsh 1980).

7. Empirical Results

7.1. Empirical Results for the Full Dataset: OLSR

The average value of price differentials in our dataset is 10 percent (see Table 2). Standard t-statistics are used to investigate whether the price differentials are significantly greater than zero. The statistic calculates to 10.87 and it provides a strong indication of positive price differentials. These results are in line with those already found in Guide & Li (2010). A similar pattern of results is obtained when the entire dataset is partitioned into the two subsamples: remanufactured products sold by manufacturer-approved and non manufacturer-approved vendors.

Seller reputation: Table 3 column 3 reports standard OLSR empirical estimates of Eq. (2) together with a battery of diagnostic tests for homoschedasticity, model specification and normality in the residuals. The impacts of both positive and negative seller reputation on price differentials have the expected signs. However, only the former explanatory variable is statistically significant. More specifically, we find that greater positive seller reputation is significantly associated with lower price differentials (α_2 =-0.028, *p-value*=0.03), and greater negative seller reputation is associated with higher price differentials (α_3 =0.0167, *p-value*=0.18). Thus, these results provide strong support for the hypothesis H_{1a} whereas for H_{1b} the evidence is weaker. Using the OLSR regression estimates and with all the other explanatory variables set at their average values, we find that an increase in positive seller feedback by 10 percent from the mean is associated with a 1.85 percent decrease in price differentials, whereas an increase by 1 standard deviation is associated with a 71 percent decrease in price differentials. We compare the magnitude of the impacts on price differentials of both positive and negative seller reputation. This is a useful exercise even though we have already seen that the latter explanatory variable is not significant at standard significance levels. Other things being equal, an increase of negative seller feedback from its mean by 10 percent and 1 standard deviation is associated, respectively, with increases of 1.08 and 133 percent in price differentials. Thus, for equal increases in the counts of positive and negative seller feedback of the order of 10 percent the impact of positive seller feedback more than offsets that of negative so that price differentials narrow. On the other hand, for equal increases of the order of 1 standard deviation price differentials widen. All in all, the above results suggest that for the UK market the positive seller reputation has a stronger impact on price differentials than negative seller reputation. It follows that sellers with poor reputation do not have to provide necessarily significant price breaks to support their selling of remanufactured products, whereas sellers with a positive reputation can benefit from narrower mark-ups. Thus, customer policies are an important key element of e-businesses such as eBay. This pattern of results is similar to those already obtained by Subramanian & Subramanyam (2012) using data on eBay US.

Length of seller incumbency, length of warranty and seller identity: The empirical results suggest that buyers are not willing to pay higher prices for remanufactured products sold by sellers with longer eBay incumbency, for remanufactured products covered by longer warranties, or for products remanufactured by manufacturer-approved vendors. The estimated parameters α_4 (-0.0086), α_5 (0.0005) and α_8 (-0.0272) present the expected sign yet are not statistically significant at standard significance levels, so we do not find any support for hypotheses H_2, H_3 and H_6 respectively.

Demand and supply proxies: Empirical results suggest that supply and demand for remanufactured products are important determinants of price differentials. In fact, we find support for hypothesis H_5, that larger quantities of remanufactured products available from sellers are associated with higher price differentials (α_7 = 0.0021, *p-value*=0.07). An increase in the quantities available by 10 percent from the mean is associated with a 0.38 percent increase in price differentials, whereas an increase by 1 standard deviation is associated with an increase of 16.12 percent. The proxy for product demand is negatively associated with price differentials (α_6=-0.0001, *p-value*=0.08), suggesting that popular remanufactured products are sold at higher prices. In other words, higher demand for remanufactured products is associated with lower price differentials. We note that an increase in demand by 10 percent is associated with a 0.54 percent decrease in price differentials, whereas an increase by 1 standard deviation is associated with a decrease of 11.86 percent. The above results suggest that both hypotheses H_4 and H_5 hold.

Listing end time/day and duration: We find that remanufactured product listings that end at weekends (Saturday or Sunday) or during night time hours (6pm until 6am) are associated with higher price differentials. The former type of listing is strongly significant whereas the latter is not (α_9 =0.1158, *p-value*=0.01 and α_{10} = 0.0277, *p-value* = 0.29, respectively). This could be attributed to more careful assessments by buyers of the competitiveness among products listed and alternative offerings during weekends or night time hours. We also control for the impact of the length of advert of listed products on price differentials and we find that it is not significant at standard significance levels (α_{11} =-0.0021, *p-value* = 0.19).

Return policy: However, buyers are willing to pay a premium for remanufactured products with an accepted return policy (α_{12}=-0.089, *p-value*=0.02). This finding supports hypothesis H_9. More specifically, we find that the availability of return policies is associated with a 46.11 percent decrease in price differentials.

Insert Table 3 about here

7.2. Empirical Results of the Full Dataset: RR and MR

Following the empirical results set out in Table 1, we compute two further measures of multicollinearity, the Variance Inflation Factor (VIF) and the Maximum Condition index. The two measures calculate, respectively, to 13.18 and 55.65 and therefore provide further supporting evidence for the presence of multicollinearity. Since the lack of statistical significance of explanatory variables such as negative seller reputation might be a by-product of multicollinearity, we re-estimate Eq. (2) by using RR and MR methodologies, which can deliver empirical estimates while controlling for an ill-conditioned information matrix. RR and MR empirical estimates are set out in the fourth and fifth column of Table 3.

More specifically, we carry out RR estimates by introducing a constant parameter *k* in the estimators of α_2 and α_3, whereas we leave unaffected the remaining cohort of parameters characterising Eq. (2). A critical aspect of the application of RR is the choice of the parameter *k*. A simple criterion used in the literature is to construct the so-called Ridge Traces, which plot the parameter estimates as functions of *k*. The potential instability in the estimates induced by multicollinearity can be assessed by looking at whether large movements in the parameter estimates occur as *k* increases in small increments from zero. It has been suggested that visual judgment of stability can be used to select the optimal value of *k*. Along with the graphical inspection we make use of a number of other criteria to estimate the optimal *k,* as proposed by Hoerl & Kennard (1970), Hoerl, Kennard & Baldwin (1975), Lawless & Wang (1976) and Kibria (2003). The first three criteria suggest a value of *k* equal to, respectively, 4.6, 3.7 and 5.1 whereas the last criterion in Kibria (2003) sets a lower value equal to 0.3.

The Ridge Trace reported in Fig. 2 plots the t-ratios for the parameters α_2 and α_3 and it shows that they are relatively stable for values of *k* larger than 0.7. Thus, we decide to report empirical estimates of RR when the parameter *k* is equal to 0.8. RR estimates of Eq. (2) (see Table 3 column 4) are very similar to the OLSR estimates in terms of both sign and magnitude of the parameters, with only small differences of the order of 10^{-3}.

Insert Fig. 2 about here

We then re-estimate Eq. (2) by using MR. Empirical estimates are carried out by feeding the estimation procedure with priors for the values of parameters taken from Subramanian & Subramanyam (2012). The empirical results are set out in the fifth column of Table 3. Also in this case, MR estimates are similar to both OLSR and RR parameters in terms of sign and magnitude, with marginal differences of the order of 10^{-3}. The similarity between OLSR, RR and MR estimates suggests that the form of multicollinearity which affects both positive and negative seller reputation does not seem to induce any significant bias in the empirical estimates of Eq. (2).

In the bottom panel of Table 3 we compute a battery of diagnostic tests to investigate whether the model of Eq. (2) is correctly specified. The F-tests for the null that all the explanatory variables are jointly not statistically significant are soundly rejected at the 1 percent level. Both the White and Goldfeld-Quandt tests fail to reject the null of heteroschedasticity at standard significance levels. Similarly, the RESET tests fail to reject the null that there are no specification errors. Finally, the Kolmogorov-Smirnov (K-S) tests reject the null of normality in the residuals at the 5 percent level. Residuals are, in fact, leptokurtic in comparison to the normal distribution. Thus, inference is carried out by assuming that the asymptotic properties of OLSR, RR and MR estimators hold. Even though the number of observations in our sample is fairly large, the finite sample properties of the above estimators might depart from their asymptotic properties, potentially leading to incorrect conclusions. We check for this possibility in Section 7.5 where we carry out a bootstrap analysis, which shows that such departures are moderate. All in all, the above statistics suggest that the model of Eq. (2) is reasonably well specified.

7.3. Empirical Results for the Two Partitioned Datasets: Non Manufacturer-Approved Vendors

The empirical results set out in Section 5 suggest that the price differentials of remanufactured products sold by manufacturer-approved and non manufacturer-approved vendors are characterised by two different data generation processes. Thus, in this Section we investigate whether the pattern of results obtained in Table 3 still holds when the entire dataset is partitioned into two subsamples.

We begin our analysis by re-estimating Eq. (2) for transactions carried out by non manufacturer-approved vendors. Standard OLSR, RR and MR estimates together with a battery of diagnostic statistics are reported in the third, fourth and fifth column of Table 4. Also in this case, the impacts of both positive and negative seller reputation on price differentials have the expected signs, with only the former explanatory variable statistically significant (α_2=-0.0395, *p-value*=0.04). Thus, greater positive reputation is significantly associated with lower price differentials. We find that an increase in positive seller feedback by 10 percent from the mean is associated with a 2.94 percent decrease in price differentials, whereas an increase by 1 standard deviation is associated with an 80.39 percent decrease. By comparing the magnitude of the impacts on price differentials between positive and negative seller reputation, price differentials narrow for equal increases of the order of 10 percent whereas price differentials widen for increases of the order of 1 standard deviation.

All in all, for non manufacturer-approved sellers the results suggest that positive seller reputation has a stronger impact on price differentials than negative seller reputation does. In addition, our empirical results suggest that buyers are willing to pay higher prices for products covered by warranties (α_5=-0.0078, *p-value*=0.03) offered by non manufacturer-approved sellers but not for products sold by those sellers who have longer eBay incumbency, or for which return policies are available.

Thus, for non manufacturer-approved vendors both seller reputation and provision of warranties are important determinants of price differentials, whereas both length of incumbency and return policy availability play negligible roles. By holding other explanatory variables equal to their means, we find that an increase by 10 percent in the length of warranty from the mean is associated with a 0.79 percent decrease in price differentials, whereas an increase by 1 standard deviation is associated with a decrease of 20.39 percent.

Empirical results suggest that the proxies of supply and demand for remanufactured products are important determinants of price differentials. Larger available quantities of remanufactured products supplied by non manufacturer-approved sellers are associated with higher price differentials (α_7 = 0.0052, *p-value*=0.01) whereas higher demand is associated with lower price differentials (α_6=-0.0002, *p-value*=0.04). The impacts of increases in supply and demand on price differentials are similar in magnitude to those reported in Section 7.1 for the unpartitioned dataset. For remanufactured products listed by non manufacturer-approved sellers we find that the end of listings during weekend is associated with higher price differentials whereas the end of listings during night time hours does not play any significant role (α_9 =0.1078, *p-value* =0.06 and α_{10} =-0.0205, *p-value* = 0.63, respectively). Unlike previous results, we find that the length of advert of listed remanufactured products by non manufacturer-approved sellers is statistically significant (α_{11} =-0.0079, *p-value*=0.01) and is negatively associated with price differentials. This last result suggests that longer periods of product listings increase the number of bids so that the price of remanufactured products can potentially increase.

Insert Table 4 about here

7.4. Empirical Results of the Two Partitioned Datasets: Manufacturer-Approved Vendors

We carry out a similar analysis by re-estimating Eq. (2) for the second partitioned dataset, which only includes transactions of remanufactured products by manufacturer-approved vendors. Empirical estimates are reported in the third, fourth and fifth column of Table 5. Surprisingly, we find that the variables that used to be significant determinants of price differentials for the full dataset as well as for the partitioned dataset of non manufacturer-approved sellers now become not significant when the partitioned dataset for manufacturer-approved vendors only is considered. Thus, the pattern of results obtained in Table 3 for the aggregate dataset is substantially driven by the trading of remanufactured products carried out by non manufacturer-approved sellers. It follows that the price differentials of manufacturer-approved sellers must be driven by different yet less obvious determinants not considered in our set of explanatory variables. Other features of the transactions of remanufactured products, such as whether the vendor is a well-established/well-known retailer, or the number of sales completed, might play an important role in the present context.

In Table 5, empirical estimates suggest that the availability of return policies is associated with a decrease in price differentials. Another important observation between the two partitioned datasets is that return policies did not seem to matter for the remanufactured products sold by non manufacturer-approved sellers, yet did matter for the remanufactured products sold by manufacturer-approved vendors. We also find that remanufactured product listings ending at weekends or during night time hours are associated with higher price differentials.

Finally, we re-estimate Eq. (2) on the partitioned datasets by using RR and MR methods. Empirical estimates are carried out by setting the parameter k = 0.8 and by feeding in the MR estimators with priors taken from the parameter estimates of Table 3. The criteria previously set out suggest values of k similar to those reported for the unpartitioned dataset. Moreover, Ridge Traces show that the parameters α_2 and α_3 become relatively stable for values larger than 0.6. Such evidence holds for both the partitioned datasets. Ridge Traces and detailed computations of k are not reported to save space but are available from the authors upon request. Empirical results are set out in the fourth and fifth column of Tables 4 and 5. Both RR and MR estimates are similar to OLSR parameters in terms of signs and magnitudes, with marginal differences of the order of 10^{-3}. Thus, when the partitions of the dataset are considered, the similarity among OLSR, RR and MR estimates suggests that the presence of multicollinearity does not induce any significant bias in the estimation of Eq. (2).

Tables 4 and 5 report the diagnostic statistics for residuals when Eq. (2) is estimated on the partitioned datasets. Both the White and Goldfeld-Quandt tests fail to reject the null of homoscedasticity at standard significance levels. Similarly, the RESET statistics fail to reject the null of no specification errors whereas the F-tests reject the null that the explanatory variables are jointly not statistically significant. Also in this case, residuals are leptokurtic and K-S tests reject the null of normality at the 5 percent level. All in all, the above diagnostic tests suggest that the model of Eq. (2) is reasonably well specified when applied to the partitioned datasets.

Insert Table 5 about here

7.5. Bootstrap Analysis

The residuals obtained by carrying out OLSR, RR and MR estimates of Eq. (2) on the entire as well as partitioned datasets are leptokurtic in comparison to normal distributions. Since residuals are not well-behaved, inference is carried out by relying on the asymptotic properties of the above estimators. However, the use of asymptotic confidence intervals might lead to incorrect conclusions whenever the finite sample properties of the OLSR, RR and MR estimators depart from their asymptotic properties. Such departures, in turn, occur if the sample size is not large enough to ensure the validity of the asymptotic properties. Thus, we investigate the finite sample properties of the above estimators by carrying out a bootstrap analysis of Eq. (2). More specifically, we construct artificial datasets by bootstrapping pairs from our original dataset of 917 observations. For each bootstrapped dataset we carry out

OLSR, RR and MR estimates of Eq. (2). We then repeat the above empirical exercise 1,999 times so that we obtain the empirical distributions of the related parameters.

Such empirical distributions resemble the related normal densities, suggesting moderate departures of OLSR, RR and MR estimators from their asymptotic properties. However, K-S statistics applied to the empirical distributions of the parameters α_1, α_2, α_5, α_6, α_7 and α_{11} reject the null of normality at the 5 percent level. Given the above evidence, bootstrapped confidence intervals would be a better tool than asymptotic intervals to carry out statistical inference. The above empirical distributions are therefore used to construct bootstrapped Bias Corrected (BC) confidence intervals (see DiCiccio & Efron 1996). Such confidence intervals for OLSR, RR and MR are set out in Table 3. For purposes of comparison, we also compute the bootstrap percentile intervals as well as the asymptotic intervals. (The bootstrapped empirical distributions as well as the percentile and asymptotic intervals are not reported to save space but are available from the authors upon request). The BC intervals differ only slightly from the percentile intervals as the average bootstrap coefficients are similar to the corresponding point estimates reported in Table 3. This result suggests that there is little, if any, bias in the estimates of the parameters of Eq. (2). the BC confidence intervals are, in general, slightly narrower than asymptotic intervals, suggesting that the asymptotic standard errors set out in Table 3 are biased upward. All in all, the bootstrap analysis provides a pattern of results very similar to that obtained by applying asymptotic OLSR, RR and MR estimators. The only difference between bootstrap and asymptotic analysis relates to the parameter α_6, which now becomes not significant at the 10 percent level.

We then carry out the same bootstrap exercises for the two partitioned datasets. The BC confidence intervals are reported in Tables 4 and 5. Also in this case, the bootstrap analysis provides strong support for the pattern of results based on the asymptotic properties of OLSR, RR and MR estimators. All in all, the above results suggest that the finite sample properties of the OLSR, RR and MR estimators tend to depart from their asymptotic properties. However, such departures appear negligible and the asymptotic properties of the above estimators remain a reasonable approximation of their finite sample properties.

7.6. Robustness Checks

In this Section we carry out two different empirical exercises. Firstly, we investigate how the model of Eq. (2) compares to other competing specifications of the relationship between price differentials and the determinants previously considered. Secondly, we investigate the robustness of the estimates of Eq. (2) to small modifications in the datasets used, as well as to change in the method followed, to compute the covariance matrices.

We begin our analysis by testing whether the log-log model of Eq. (2) is preferable to two alternatives specifications, where the dependent variables PD_i and $-\ln(1\text{-}PD_i)$ are regressed against the set of explanatory variables as defined in Section 4. We refer to the first alternative as the additive model and to the second as the log-lin model. More specifically, we use the PE statistics to test for the null that the additive model is not preferable to Eq. (2), and vice versa (see MacKinnon, White & Davidson (1983)). The comparison between the log-log and log-lin model is carried out by means of both the J and JA statistics. These last are used to test for the null that the log-lin model is not preferable to Eq. (2), and vice versa (see Davidson & MacKinnon (1981)).

The PE tests cannot reject either the null that the log-log is not better than the additive model or vice versa. As a result, both these specifications appear to be appropriate to explain the relationship between price differentials and their determinants. However, when the White, the Goldfeld-Quandt and the RESET tests are applied to the residuals generated by the additive model, both the null of homoschedasticity and correct functional form are rejected at the 1 percent level. This last result suggests that the log-log model of Eq. (2) should be preferred to the additive model.

We then use both the J and JA tests to evaluate whether Eq. (2) is preferred to the log-lin specification, and vice versa. On the one hand, both the statistics reject the null that Eq. (2) is not better than the log-lin model at the 5 and 10 percent level respectively. On the other hand, the null that the log-lin specification is not better than Eq. (2) cannot be rejected at standard significance levels. All in all, the PE, J and JA statistics suggest that the log-log specification of Eq. (2) should be preferred to both the additive and log-linear models. When the above tests are applied to the partitioned datasets we obtain a very similar pattern of results.

We then carry out a number of robustness checks for the OLSR, RR and MR empirical estimates previously obtained. We initially re-estimate Eq. (2) by using an alternative heteroschedasticity consistent estimator of the covariance matrix proposed by Davidson and MacKinnon (1993). Secondly, we carry out empirical estimates of Eq. (2), where the dependent variable is restricted to assume positive values only. By dropping the transactions for which the dependent variable is negative we reduce the number of observations from 917 to 649. Thirdly, we conduct a similar estimation exercise on a restricted dataset in which $POSREP_i$ assumes values within its mean plus/minus three times its standard deviation. In this case, the number of observations available drops to 770. The above exercises enable us to investigate whether the pattern of results previously obtained are driven by the presence of negative price differentials or outliers in the measure of positive reputation. Fourthly, we replace in Eq. (2) the separate positive and negative reputation measures with a single reputation score calculated as the difference between the two. All in all, the empirical results obtained suggest that the sign, magnitude and statistical significance of the estimated parameters are consistent with those set out in Tables from 3 to 5. Finally, we supplement Eq. (2) with squared values of positive feedback counts as well as with interactions among this last variable, negative feedback counts and seller identity. Empirical estimates suggest that all these terms are not statistically significant. The above empirical exercises are then repeated for the two partitioned datasets and we get results very similar to those obtained for the full sample. (Please note the above empirical results are not reported but are available from the authors upon request.)

8. Conclusions

We studied the market determinants of price differentials between new and corresponding remanufactured products in Electronics by using data on purchases made on eBay UK. We carried out the empirical analysis by using Ordinary Least Squares Regression, Ridge Regression (RR) and Mixed Regression (MR) methods to deal with the statistical issue of collinearity among explanatory variables. Our empirical results suggest that seller positive reputation, the length of warranties, the proxies of demand and supply of remanufactured products, the duration and end day of product listings as well as the availability of return policies are important market determinants of price differentials. More specifically, we find that seller identity (i.e. manufacturer-approved or non manufacturer-approved vendors) plays an important role, as our empirical results are predominantly driven by transactions carried out by non manufacturer-approved vendors. We can conclude that the price differentials of remanufactured products listed by manufacturer-approved sellers must be driven by a different set of determinants not available in our dataset. This leads to an interesting area of further study to investigate these less obvious market determinants for remanufactured product transactions carried out by manufacturer-approved vendors.

References

Agrawal, V. V., A. Atasu, and K. van Ittersum. 2012. “Remanufacturing, third-party competition and consumers' perceived value of new products.” Working paper, Georgetown University McDonough School of Business.

Ahn, H-D., D-H. Lee, and H-J. Kim. 2011. “Solution algorithms for dynamic lot-sizing in remanufacturing systems.” *International Journal of Production Research* 49 (22), 6729-6748.

Annaert J., A. Claes, M. De Ceuster, and H. Zhang. 2013. “Estimating the spot rate curve using the Nelson-Siegel model: A Ridge Regression approach.” *International Review of Economics and Finance* 27: 482-496.

Atasu, A., V. D. R. Guide, Jr., and L. N. Van Wassenhove. 2008. “Product Reuse Economics in Closed-Loop Supply Chain Research.” *Production and Operations Management* 17 (5): 483-496.

Athey, S., and P. Haile. 2002. “Identification in standard auction models.” *Econometrica* 70 (6): 2170-2140.

Bajari, P., and A. Hortaçsu. 2003. “Cyberspace Auctions and Pricing Issues, A Review of Empirical Findings.” In *New Economy Handbook*, edited by D. Jones. Elsevier, San Diego, CA.

Barnett, A., and E. Eisen. 1982. “A quartile test for differences in distribution.” *Journal of American Statistical Association* 77 (377), 47-51.

Belsey, D.A., E. Kuh, and R. E. Welsch. 1980. *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*. New York, John Wiley & Sons.

British Standards., 2009. Design for manufacture, assembly, disassembly and end-of-life processing. Terms and definitions. BSI, London, BS 8887-2.

Buday, T. 1989. “Capitalizing on brand extensions.” *Journal of Consumer Marketing*, 6 (4), 27-30.

Cabral, L., and A. Hortaçsu. 2010. “The Dynamics of Seller Reputation: Evidence from eBay.” *Journal of Industrial Economics* 58 (1), 54-78.

Corbett, C.J., and P. R. Kleindorfer. 2001a. “Environmental Management and

Operations Management: Introduction to Part 1 (Manufacturing and Eco-Logistics).” *Production and Operations Management* 10 (2), 107-111.

Corbett, C. J., and P. R. Kleindorfer. 2001b. “Environmental Management and Operations: Introduction to Part 2 (Integrating Operations and Environmental Management Systems).” *Production and Operations Management* 10 (3), 225-227.

Davidson, R., and J. MacKinnon. 1993. *Estimation and Inference in Econometrics*. Oxford: Oxford University Press.

Davidson, R. and J. MacKinnon. 1981. “Several Tests for Model Specification in the Presence of Alternative Hypotheses.” *Econometrica* 49 (3), 781-793.

DiCiccio, T., J. and B. Efron. 1996. “Bootstrap Confidence Intervals.” *Statistical Sciences* 11 (3), 189-229.

Eaton, D.H. 2007. “The Impact of Reputation, Timing, and Source on Auction Outcomes.” *The B. E. Journal of Economic Analysis and Policy* **7** (1), 1-14.

Ferguson, M., and L. B. Toktay. 2006. “The Effect of Competition on Recovery Strategies.” *Production and Operations Management* 15 (3), 351-368.

Ferrer, G., and J. M. Swaminathan. 2006. “Managing New and Remanufactured Products.” *Management Science* 52 (1), 15-26.

Ghilagaber, G. 2004. “Another look at Chow’s test for the equality of two heteroscedastic regression models.” *Quality and Quantity* 38 (1), 81-93.

Grubbström, R. W., and O. Tang. 2006. “Optimal production opportunities in a remanufacturing system.” *International Journal of Production Research* 44 (18-19), 3953-3966.

Guide, Jr. V. D. R., and L. N. Van Wassenhove. 2006a. “Closed-Loop Supply Chains: An Introduction to the Feature Issue (Part 1).” *Production and Operations Management* 15 (3), 345–350.

Guide, Jr. V. D. R., and L. N. Van Wassenhove. 2006b. “Closed-Loop Supply Chains: An Introduction to the Feature Issue (Part 2).” *Production and Operations Management* 15 (4), 471–472.

Guide, Jr. V. D. R., and L. N. Van Wassenhove. 2009. “The Evolution of Closed-Loop Supply Chain Research.” *Operations Research* 57 (1), 10-18.

Guide, Jr. V. D. R., and J. Li. 2010. “The Potential for Cannibalization of New Product Sales by Remanufactured Products.” *Decision Sciences* 41 (3), 547-572.

Hoerl, A. E., and R. W. Kennard. 1970. “Ridge Regression: Biased estimation for non-orthogonal problems.” *Technometrics* 12 (1), 55-67.

Hoerl, A. E., R. W. Kennard, and K. F. Baldwin. 1975. “Ridge Regression: some simulations.” *Communication in Statistics* 4 (2), 105-123.

Houser, D., and J. Wooders. 2006. “Reputation in Auctions: Theory and Evidence from eBay.” *Journal of Economics and Management Strategy* 15 (2), 353–369.

Kibria, G. 2003. “Performance of some new ridge regression estimators.” *Communication in Statistics* 32 (2), 419-435.

Kleindorfer, P. R., K. Singhal, and L. N. Van Wassenhove. 2005. “Sustainable Operations Management.” *Production and Operations Management* 14 (4), 482–492.

Lawless, J. F., and P. Wang. 1976. “A simulation study of ridge and other regression estimators.” *Communications in Statistics – Theory and Methods* 5 (4), 307–323.

Livingston, J. 2005. “How Valuable is a Good Reputation? A Sample Selection Model of Internet Auctions.” *The Review of Economics and Statistics* 87 (3), 453-465.

Lucking-Reiley, D., D. Bryan, N. Prasad, and D. Reeves. 2007. “Pennies from eBay: The Determinants of Price in Online Auctions.” *Journal of Industrial Economics* 55 (2), 223-233.

Lund, R.T. 1996. *The remanufacturing industry: Hidden giant*. Boston: Boston University.

MacKinnon, J., H. White and R. Davidson. 1983. “Several Tests for Model Specification in the Presence of Alternative Hypotheses: Some Further Results.” *Journal of Econometrics* 21 (1), 53-70.

Mason, C. H., and G. R. Milne. 1994. “An approach for identifying cannibalization within product line extensions and multi-brand strategies." *Journal of Business Research*, 31 (2-3), 163-170.

Melnick, M. I., and J. Alm. 2002. "Does a Seller's Reputation Matter? Evidence from eBay Auctions." *Journal of Industrial Economics* 50 (3), 337–350.

Nakashima, K., H., Arimitsu, T. Nose, and S. Kuriyama. 2004. "Optimal control of a remanufacturing system." *International Journal of Production Research* 42 (17), 3619-3625.

Ovchinnikov, A. 2011. "Revenue and Cost Management for Remanufactured Products." *Production and Operations Management* 20 (6), 824-840.

Parker, D. (2004) "Remanufacturing in the UK: a significant contributor to sustainable development?" RRF, North Yorkshire. Available at: http://www.remanufacturing.org.uk/free-reuse-publication.lasso?report=48. Accessed 14/11/2012.

Resnick, P., and R. Zeckhauser. 2002. "Trust Among Strangers in Internet Transactions: Empirical Analysis of eBay's Reputation System." *Advances in Applied Microeconomics* 11, 127-157.

Resnick, P., R. Zeckhauser, J. Swanson, and K. Lockwood. 2006. "The Value of Reputation on eBay: A Controlled Experiment." *Experimental Economics* 9, 79–101.

Simonsohn, U. 2010. "eBay's Crowded Evenings: Competition Neglect in Market Entry Decisions." *Management Science* 56 (7), 1060-1073.

Standifird, S. S. 2001. "Reputation and E-Commerce: Ebay Auctions and the Asymmetrical Impact of Positive and Negative Ratings." *Journal of Management* 27, 279–295.

Subramanian, R., and R. Subramanyam. 2012. "Key factors in the market for remanufactured products." *Manufacturing & Service Operations Management* 14 (2), 315-326.

Tang, O. R. W. Grubbström, and S. Zanoni. 2004. "Economic evaluation of disassembly processes in remanufacturing systems." *International Journal of Production Research* 42 (17), 3603-3617.

Theil, H. 1971. "Principles of Econometrics." John Wiley and Sons, New York.

U.S. EPA (Environmental Protection Agency). 1997. "Remanufactured products: Good as new." EPA530-N-002, Washington DC.

U.S. EPA (Environmental Protection Agency). 1998. "Macroeconomic importance of recycling and remanufacturing (October 28)." Available at: http://yosemite.epa.gov/ee/epa/ria.nsf/vwAN/S98-27.pdf/$file/S98-27.pdf. Accessed 29/06/2013.

U.S. EPA (Environmental Protection Agency). 2011. "National Strategy for Electronics Stewardship (July 20)." Available at: http://www.epa.gov/osw/conserve/downloads/elec_fs.pdf. Accessed 29/06/2013.

Table headings and figure captions

Table 1 Descriptive statistics and correlation indices

Table 2 Price differentials: basic statistics

Table 3 Linear regressions for log transformation of price differentials

Table 4 Linear regressions for log transformation of price differentials sorted according to indicator variable $MANUF_i$=0.

Table 5 Linear regressions for log transformation of price differentials sorted according to indicator variable $MANUF_i$=1.

Figure 1 Empirical probability distribution functions of price differentials for manufacturer-approved sellers (solid line) and non manufacturer-approved sellers (dotted line)

Figure 2 Ridge Trace for the t-ratios of parameters α_2 (ln($POSREP_i$) solid line) and α_3 (ln($NEGREP_i$) dotted line) estimated on the unpartitioned dataset. Values of the statistics reported on the vertical axis and values of k on the horizontal axis.

Table 1 Descriptive statistics and correlation indices

	POSREP	NEGREP	INCUMB	WARR	SUP	DEMAND	MANUF	DURAT	WKND	NIGHT	RETURN
Mean	9803	57	1635	1.615	2.534	70.460	0.525	8.231	0.300	0.486	0.555
Std Error	51628	573	1231	3.703	10.034	171.600	0.500	14.429	0.458	0.571	0.497
Min	0	0	13	0	1	0	0	1	0	0	0
Max	815446	9904	4932	24	213	2614	1	192	1	8	1
Observations	917	917	917	917	917	917	917	917	917	917	917
POSREP	1.000										
NEGREP	0.946	1.000									
INCUMB	0.227	0.132	1.000								
WARR	0.163	0.029	0.126	1.000							
SUP	0.119	0.045	0.025	0.121	1.000						
DEM	-0.016	-0.007	0.057	0.004	0.335	1.000					
MANUF	0.082	0.059	0.097	0.080	0.004	-0.055	1.000				
DURAT	0.040	-0.005	0.106	0.071	0.313	0.154	0.085	1.000			
WKND	0.008	0.031	0.114	-0.044	-0.024	0.076	-0.049	0.038	1.000		
NIGHT	-0.039	-0.023	-0.019	-0.060	-0.057	-0.044	-0.034	-0.093	0.051	1.000	
RETURN	0.167	0.087	0.178	0.341	0.126	0.070	-0.141	0.193	-0.037	-0.083	1.000
Eigenvalues	2.198	1.647	1.219	1.121	1.088	0.95	0.813	0.794	0.608	0.52	0.039

Notes:

Descriptive statistics for the explanatory variables included in Eq. (2) (see Section 6).

Table 2 Price differentials: basic statistics

	Price Differentials Include both manufacturer-approved and non manufacturer-approved vendors	**Price Differentials** ($MANUF_i$ = 1) Only include manufacturer-approved vendors	**Price Differentials** ($MANUF_i$ = 0) Only include non manufacturer-approved vendors
Mean	0.100	0.094	0.109
SD	0.281	0.251	0.312
t-stat[1]	10.87 (0.000)	8.198 (0.000)	7.303 (0.000)
Observations	917	481	436
Equality Mean[2]		-0.595 (0.302)	
Equality Median[3]		-1.864 (0.031)	
Equality Variance[4]		18.38 (0.000)	
Equality Distrib[5]		27.22 (0.000)	
K-S Test[6]		0.111 (0.000)	
Chow Test[7]		34.42 (0.000)	

Notes:

1. t-statistics for the null of population mean equals to 0.
2. 2-sample t-statistics for the null of equality in mean. P-value in parentheses.
3. Mann-Whitney Test for the null of equality in median. P-value in parentheses.
4. Levene test for the null of equality in variance. P-value in parentheses.
5. Barnett & Eisen (1982) test for the null of equality in distribution. P-value in parentheses.
6. Kolmogorov-Smirnov Test for the null of equality in distribution. P-value in parentheses.
7. Chow Test for the null of equality between two sets of coefficients in two linear regression models. P-value is in parenthesis. Test is computed by fitting Eq. (2) to the two partitioned datasets.

Table 3 Linear regressions for log transformation of price differentials

Explanatory Variable	Parameter	Log-Normal Regression	Ridge Regression	Mixed regression
POSREP (ln)	α_2	-0.028**	-0.028**	-0.028**
		(0.0128)	(0.0128)	(0.0128)
		[-0.0526; -0.0100]	[-0.0517; -0.0085]	[-0.0511; -0.0067]
NEGREP (ln)	α_3	0.0167	0.0166	0.0167
		(0.0125)	(0.0125)	(0.0125)
		[-0.0030; 0.0388]	[-0.0038; 0.0374]	[-0.0042; 0.0378]
INCUMB (ln)	α_4	-0.0086	-0.0087	-0.0086
		(0.0231)	(0.0231)	(0.0231)
		[-0.0469; 0.0288]	[-0.0478; 0.0274]	[-0.0493; 0.0281]
WARR	α_5	0.0005	0.0005	0.0005
		(0.0036)	(0.0036)	(0.0036)
		[-0.0039; 0.0085]	[-0.0043; 0.0077]	[-0.0041; 0.0091]
DEM (ln)	α_6	-0.0001*	-0.0001*	-0.0001*
		(0.00006)	(0.00006)	(0.00006)
		[-0.0001; 0.0002]	[-0.0002; 0.0001]	[-0.0002; $6x10^{-6}$]
SUP (ln)	α_7	0.0021*	0.0021*	0.0021*
		(0.0012)	(0.0012)	(0.0012)
		[0.0004; 0.0041]	[0.0017; 0.0038]	[0.0008; 0.0042]
MANUF	α_8	-0.0272	-0.0272	-0.0272
		(0.0336)	(0.0336)	(0.0336)
		[-0.0871; 0.0279]	[-0.0808; 0.0330]	[-0.0800; 0.0308]
WKND	α_9	0.1158**	0.1157**	0.1157**
		(0.0451)	(0.0451)	(0.0450)
		[0.0510; 0.1989]	[0.0488; 0.1964]	[0.0438; 0.1966]
NIGHT	α_{10}	0.0277	0.0277	0.0277
		(0.0261)	(0.0261)	(0.0261)
		[-0.0128; 0.0973]	[-0.0140; 0.0958]	[-0.008; 0.0971]
DURAT	α_{11}	-0.0021	-0.0021	-0.0021
		(0.0016)	(0.0016)	(0.0016)
		[-0.0047; 0.0005]	[-0.0048; 0.0003]	[-0.0047; 0.0004]
RETURN	α_{12}	-0.0893**	-0.0894**	-0.0893**
		(0.0393)	(0.0393)	(0.0393)
		[-0.1508; -0.0215]	[-0.1545; -0.0229]	[-0.1470; -0.0176]
Intercept	α_1	0.4234***	0.4234***	0.4244***
		(0.1471)	(0.1470)	(0.1471)
		[0.1887; 0.6714]	[0.1767; 0.6679]	[0.1917; 0.6788]
Model Fit[1]		37.35	37.35	40.78
		(0.000)	(0.000)	(0.000)
White Heter[2]		64.63	64.66	64.37
		(0.175)	(0.174)	(0.181)
G-Q Heter[3]		0.911	0.911	1.091

	(0.836)	(0.835)	(0.163)
RESET Test[4]	2.564	2.565	2.563
	(0.078)	(0.078)	(0.078)
K-S Test[5]	0.19	0.19	0.19
	(0.030)	(0.030)	(0.030)
R^2	0.166	0.166	0.166
Observations	917	917	917

Notes: dependent variable defined as -ln(1-PD_i) where PD_i is the price differential for observation i.

* (**) [***] Significant at 10 (5) [1] percent. Standard deviations of parameter estimates in parentheses.

Bias corrected confidence internals based on 1,999 bootstrap in squared brackets.

Ridge regression estimated with parameter k=0.8.

Mixed regression estimated with priors taken from Subramanian and Subramanyam (2012).

1 F-test for the null that all the regressions are jointly not statistically significant. P-value in parentheses.

2 White test for the null of homoschedasticity. P-value in parentheses.

3 Goldfeld-Quandt test for the null of homoschedasticity (data sorted by MANUF). P-value in parentheses.

4 RESET test for the null of no specification errors. P-value in parentheses.

5 Kolmogorov-Smirnov test for the null of normality. Critical value at 5 percent in parentheses.

Table 4 Linear regressions for log transformation of price differentials sorted according to indicator variable *$MANUF_i$*=0.

Explanatory Variable	Parameter	Log-Normal Regression	Ridge Regression	Mixed regression
POSREP (ln)	α_2	-0.0395**	-0.0394**	-0.0395**
		(0.0197)	(0.0196)	(0.0196)
		[-0.0728; -0.0092]	[-0.0779; -0.0108]	[-0.0753; -0.0097]
NEGREP (ln)	α_3	0.0179	0.0179	0.0179
		(0.0206)	(0.0206)	(0.0206)
		[-0.0155; 0.0531]	[-0.0158; 0.0532]	[-0.0157; 0.0538]
INCUMB (ln)	α_4	-0.0017	-0.0018	-0.0018
		(0.0329)	(0.0328)	(0.0329)
		[-0.0566; 0.0499]	[-0.0586; 0.0511]	[-0.0575; 0.0523]
WARR	α_5	-0.0078**	-0.0078**	-0.0078**
		(0.0035)	(0.0035)	(0.0035)
		[-0.0139; -0.0018]	[-0.0142; -0.0017]	[-0.0141; -0.0019]
DEM (ln)	α_6	-0.0002**	-0.0002**	-0.0018**
		(0.00009)	(0.00009)	(0.00009)
		[-0.0004; -0.00001]	[-0.0004; -0.00003]	[-0.0004; -0.00003]
SUP (ln)	α_7	0.0052***	0.0051***	0.0052***
		(0.0019)	(0.0019)	(0.0019)
		[0.0028; 0.0099]	[0.0022; 0.0099]	[0.0028; 0.0098]
MANUF	α_8	-	-	-
		(-)	(-)	(-)
WKND	α_9	0.1078*	0.1078*	0.1079*
		(0.0581)	(0.0581)	(0.0579)
		[0.0150; 0.2106]	[0.0159; 0.2129]	[0.0194; 0.2096]
NIGHT	α_{10}	-0.0205	-0.0205	-0.0204
		(0.0432)	(0.0434)	(0.0431)
		[-0.0928; 0.0630]	[-0.0873; 0.0642]	[-0.0939; 0.0614]
DURAT	α_{11}	-0.0079***	-0.0079***	-0.0078***
		(0.0029)	(0.0030)	(0.0030)
		[-0.0149; -0.0039]	[-0.0150; -0.0040]	[-0.0152; -0.0040]
RETURN	α_{12}	-0.0632	-0.0633	-0.0632
		(0.0594)	(0.0594)	(0.0595)
		[-0.1622; 0.0379]	[-0.1568; 0.0434]	[-0.1546; 0.0371]
Intercept	α_1	0.5002**	0.5002**	0.5002**
		(0.2184)	(0.2181)	(0.2183)
		[0.1646; 0.8723]	[0.1630; 0.8878]	[0.1599; 0.8672]
Model Fit[1]		30.93	30.93	30.94
		(0.000)	(0.000)	(0.000)
White Heter[2]		56.37	56.37	56.37
		(0.164)	(0.164)	(0.164)

RESET Test[3]	1.372	1.372	1.372
	(0.254)	(0.254)	(0.291)
K-S Test[4]	0.155	0.155	0.155
	(0.043)	(0.043)	(0.043)
R^2	0.21	0.21	0.21
Observations	436	436	436

Notes: dependent variable defined as -ln(1-PD_i) where PD_i is the price differential for observation i.

* (**) [***] Significant at 10 (5) [1] percent. Standard deviations of parameter estimates in parentheses.

Bias corrected confidence internals based on 1,999 bootstrap in squared brackets.

Ridge regression estimated with parameter *k*=0.8.

Mixed regression estimated with priors taken from empirical estimates of Table 3.

1 F-test for the null that all the regressions are jointly not statistically significant. P-value in parentheses.

2 White test for the null of homoschedasticity. P-value in parentheses.

3 RESET test for the null of no specification errors. P-value in parentheses.

4 Kolmogorov-Smirnov test for the null of normality. Critical value at 5 percent parentheses.

Table 5 Linear regressions for log transformation of price differentials sorted according to indicator variable *MANUF*$_i$=1.

Explanatory Variable	**Parameter**	**Log-Normal Regression (SD in parenthesis)**	**Ridge Regression (SD in parenthesis)**	**Mixed regression (SD in parenthesis)**
POSREP (ln)	α_2	-0.0188	-0.0188	-0.0188
		(0.0172)	(0.0171)	(0.0171)
		[-0.0536; 0.0065]	[-0.0500; 0.0075]	[-0.0508; 0.0099]
NEGREP (ln)	α_3	0.0121	0.0121	0.0121
		(0.0159)	(0.0159)	(0.0160)
		[-0.0144; 0.0413]	[-0.0163; 0.0397]	[-0.0165; 0.0403]
INCUMB (ln)	α_4	-0.0133	-0.0133	-0.0133
		(0.0315)	(0.0315)	(0.0315)
		[-0.0696; 0.0373]	[-0.0705; 0.0359]	[-0.0753; 0.0346]
WARR	α_5	0.0036	0.0036	0.0036
		(0.0056)	(0.0056)	(0.0056)
		[-0.0041; 0.0164]	[-0.0035; 0.0173]	[-0.0036; 0.0178]
DEM (ln)	α_6	-0.00006	-0.00006	-0.00006
		(0.0001)	(0.0001)	(0.0001)
		[-0.0003; 0.0001]	[-0.0003; 0.0001]	[-0.0003; 0.0001]
SUP (ln)	α_7	0.0015	0.0014	0.0015
		(0.0016)	(0.0016)	(0.0019)
		[-0.0010; 0.0059]	[-0.0008; 0.0061]	[-0.0011; 0.0066]
MANUF	α_8	-	-	-
		(-)	(-)	(-)
WKND	α_9	0.129*	0.129*	0.1289*
		(0.0688)	(0.0688)	(0.0687)
		[0.0306; 0.2596]	[0.0325; 0.2688]	[0.0317; 0.2725]
NIGHT	α_{10}	0.0606*	0.0606*	0.0606*
		(0.0348)	(0.0348)	(0.0347)
		[0.0118; 0.1689]	[0.0136; 0.1682]	[0.0106; 0.1753]
DURAT	α_{11}	-0.001	-0.0009	-0.001
		(0.0016)	(0.0016)	(0.0016)
		[-0.0042; 0.0012]	[-0.0038; 0.0015]	[-0.0041; 0.0015]
RETURN	α_{12}	-0.1059**	-0.1059**	-0.1059**
		(0.0524)	(0.0524)	(0.0524)
		[-0.1850; -0.0161]	[-0.1882; -0.0105]	[-0.1945; -0.0103]
Intercept	α_1	0.3513*	0.3511*	0.3513*
		(0.1909)	(0.1909)	(0.1908)
		[0.0508; 0.6905]	[0.0517; 0.6947]	[0.0726; 0.7371]
Model Fit[1]		21.02	21.02	21.04
		(0.021)	(0.021)	(0.021)
White Heter[2]		49.61	49.61	49.62
		(0.644)	(0.644)	(0.642)

RESET Test[3]	2.8	2.028	2.026
	(0.063)	(0.132)	(0.133)
K-S Test[4]	0.219	0.220	0.225
	(0.040)	(0.040)	(0.040)
R^2	0.144	0.144	0.144
Observations	481	481	481

Notes: dependent variable defined as -ln(1-PD_i) where PD_i is the price differential for observation i.

* (**) [***] Significant at 10 (5) [1] percent. Standard deviations of parameter estimates in parentheses.

Bias corrected confidence internals based on 1,999 bootstrap in squared brackets.

Ridge regression estimated with parameter k=0.8

Mixed regression estimated with priors taken from empirical estimates of Table 3.

1 F-test for the null that all the regressions are jointly not statistically significant. P-value in parentheses.

2 White test for the null of homoschedasticity. P-value in parentheses.

3 RESET test for the null of no specification errors. P-value in parentheses.

4 Kolmogorov-Smirnov test for the null of normality. Critical value at 5 percent in parentheses.

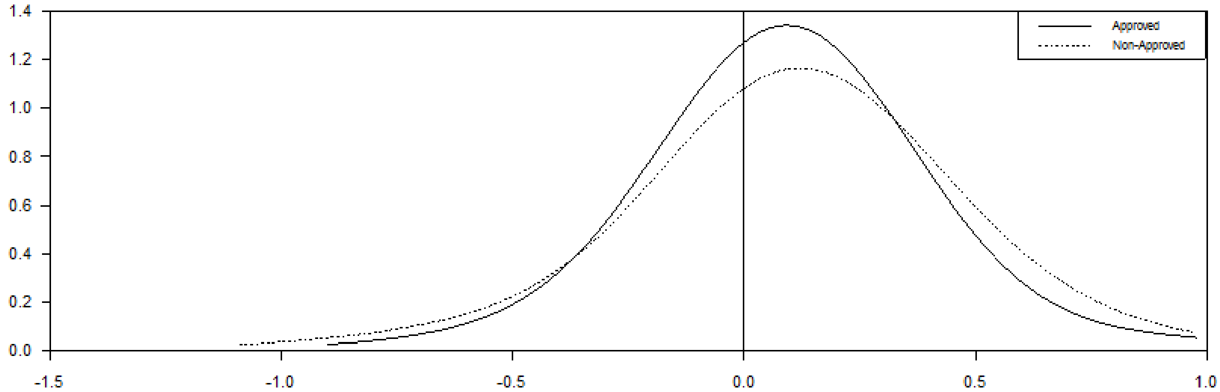

Figure 1 Empirical probability distribution functions of price differentials for manufacturer-approved sellers (solid line) and non manufacturer-approved sellers (dotted line)

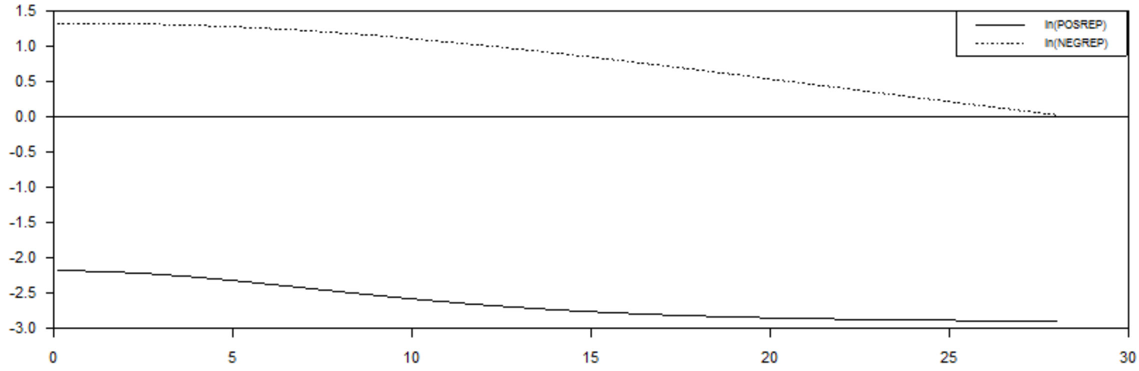

Figure 2 Ridge Trace for the t-ratios of parameters α_2 (ln($POSREP_t$) solid line) and α_3 (ln($NEGREP_t$) dotted line) estimated on the unpartitioned dataset. Values of the statistics reported on the vertical axis and values of k on the horizontal axis.