Price determinants for remanufactured products: a Case Study of eBay UK

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Abstract
Recent studies on Closed-Loop Supply Chains have highlighted the need of empirical research to identify the relative importance of market determinants. In this paper we shed light on 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 seller positive reputation, the length of warranties, the proxies of demand and supply of remanufactured products, the duration and end day of remanufactured product listings are important determinants of price differentials. Most importantly, we find seller identity plays an important role as our empirical results are predominantly driven by transactions carried out by non manufacturer-approved vendors.

Key words
Closed-Loop Supply Chains, Remanufacturing, Price differentials, Regression methods, Collinearity.

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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 vendors, and non manufacturer-approved sellers. The potential benefits of remanufacturing are twofold. First, it extends the useful life of a product, thus reduces 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, i.e. 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 accounted 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 revealed 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).

Guide & Van Wassenhove (2006a, 2009), and Atasu et al. (2008), in their recent reviews of Closed-Loop Supply Chains (CLSCs) research, stressed the need for research exploring empirical studies of market factors in CLSCs. As noted in Guide & Van Wassenhove (2009), research has barely begun to investigate market-related issues. A lack of understanding of prices and markets poses barriers to the viability of remanufacturing efforts despite the well-designed operational system (Guide & Van Wassenhove 2009, p.16). Guide & Van Wassenhove (2009) also note the opportunity for such work to lead industry practice since industry has long operated under common wisdom rather than systematic empirical studies. Inevitably, the work of investigating market-related issues would enable the development of more sophisticated and relevant analytical models (e.g. Corbett & Kleindorfer 2001a, 2001b, Guide & Van Wassenhove 2006a, 2006b, Kleindorfer et al. 2005).

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 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 within our dataset. Our empirical results suggest that seller positive reputation, the length of warranties provided for remanufactured products, the proxies of demand and supply of remanufactured products, the duration and end day of remanufactured product listings are important determinants of price differentials between new and corresponding remanufactured products. Most importantly, we find that seller identity plays an important role as the above empirical results are predominantly driven by transactions carried out by non manufacturer-approved vendors.

The remainder of the paper is organised as follows. In Section 2, we discuss the empirical works on market factors in CLSCs. Section 3 and 4 describe our datasets and the variables considered in our empirical analysis. In Section 5 and 6 we report the results from our preliminary analysis, and introduce the empirical model and the methodologies employed. In Section 7 we set out the empirical results together with a number of robustness checks. Section 8 concludes the paper.

2. Empirical Work on Market Factors in CLSCs

Guide & Li (2010) study 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. For the consumer product, consumers' willingness to pay for the remanufactured product is 15.3% lower than that for the new product, and the cannibalisation is not a concern. For the commercial product, consumers' willingness to pay for the remanufactured product is 9.7% lower than that for the new product and a certain degree of cannibalisation exists. However, for the commercial product it is not conclusive that cannibalisation of new product sales by remanufactured products exists because of the significant presence of third-party resellers.

Ovchinnikov (2011) studies pricing and remanufacturing strategy of a firm that offers both new and remanufactured versions of its product. 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. This key modelling parameter – the fraction of consumers has an inverted-U shape: it first increases and subsequently decreases when the price of a remanufactured product becomes very low. Despite the fact that a larger portion of consumers are willing to purchase products lower than their reference price, some consumers who are unwilling to purchase products under their reference price may infer the quality of the remanufactured product based on the very low price.

More recently, Agrawal, Atasu & Ittersum (2012) investigated how the presence of remanufactured products and the identity of the remanufacturer (an OEM-remanufacturer/ a third-party remanufacturer) influence the perceived value of new products. MP3 players (Apple iPod Nanos) and consumer printers (HP Laser-Jet P1006) are chosen as the product categories. Through behavioural laboratory experiments, in the absence of a third-party remanufacturer the authors found the presence of products remanufactured and sold by the OEM reduces the perceived value of new products.

Subramanian & Subramanyam (2012) study market factors, such as seller reputation, identity of sellers of remanufactured products, and warranty strength, explained the purchase price differentials between new and remanufactured products. The authors report seller reputation significantly explains the price differentials between new and remanufactured product. Remanufactured products listed by OEMs or their authorised factories are sold at relatively higher prices than product remanufactured by individual sellers who do not hold any OEM's remanufacturing authorisation. 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.

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 effect on used product prices. Although remanufactured products differ significantly from used products, the aforementioned literature signalises that seller reputation would significantly explain price differentials between new and remanufactured products. Subramanian & Subramanyam (2012) report that positive (negative) seller reputation for remanufactured products is negatively (positively) associated with price differentials. 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 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. As suggested by Cabral & Hortaçsu (2010), Resnick & Zeckhauser (2002) that market participants perceive neutral feedback negatively, we combine the total number of neutral and negative feedback counts as a measure of seller negative reputation.

2.2. Seller Identity

Within eBay UK Electronics category, there are two types of sellers listing remanufactured products: the manufacturer-approved vendors (professionally restore products to working order) and non manufacturer-approved sellers (restore items to working order, yet these sellers are not approved by the manufacturers). 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 between manufacturer-approved vendors and non manufacturer-approved sellers. Ferrer & Swaminathan (2006) assume in their analytical models that consumers have a higher preference for remanufactured products offered by manufacturer-approved vendors, whereas in Ferguson & Toktay (2006) consumers do not differentiate the remanufactured product offered by either manufacturer-approved or not-approved 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.

2.3. Remanufactured Product Warranty

Product warranty is an important element to take into account 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, in the presence of seller reputation and remanufacturer identity, that stronger warranties are not significantly associated with higher prices paid for remanufactured products.

2.4. Demand and Supply Proxies

For manufacturer-approved vendors 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 of a remanufactured product does not only help set either the reserve or buy-it-now price, but also gain a good understanding of what remanufactured products are on demand. Subramanian & Subramanyam (2012) find that a greater quantity of remanufactured product 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.

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 a SQL database, making it possible to search and export data easily. The methodology adopted revolves three main steps. First, a list of Electronics subcategories consists of 26 subcategories is compiled (See Table 1). Next, the application uses eBay's APIs to retrieve listings of products for each subcategory. Although it is possible to impose filters in the list, we do not apply them as we intend to randomly select products 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.

Insert Table 1 about here.

Across all product categories on eBay UK, the Electronics product category contains a significant number of both new and corresponding remanufactured products. Table 1 summarises all subcategories of Electronics product category. 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 such sellers who list multiple adverts for the same remanufactured product.

We then partition our entire dataset into two subsamples. The former encompasses the Electronics products remanufactured by manufacturer-approved vendors and it consists of 481 transactions. The latter contains the products remanufactured by non manufacturer-approved sellers and it 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.

4. Variables

4.1 Dependent Variable: Price Differentials

We denote the price differential of a remanufactured product transaction as PD_t. We compute the price differentials PD_t, $t = \{1, 2, \ldots, 917\}$ 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:

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

Here, the price of a new or a corresponding remanufactured product 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 transaction *t*, we use the number of positive feedback counts ($POSREP_t$) as a measure of seller positive reputation, and the number of negative and neural feedback counts ($NEGREP_t$) as a measure of seller negative reputation. This enables 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 $INCUMB_t$ 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' incumbencies are 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

$WARR_t$ 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 higher price differentials.

Demand and supply proxies: We expect demand and supply factors to exercise 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_t), whereas the available quantity of the remanufactured product is referred to as a supply proxy (SUP_t). In this case the null that we test are the followings:

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 $MANUF_t$ 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 a 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 $DURAT_t$ measured as 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). A reason is the potentially closer attention paid by buyers during weekends or night time (non-work) hours. Accordingly, we control for these patterns by considering two dummy indicators: $WKND_t$, which captures whether the listing end time for a remanufactured product transaction was at weekends (Saturday or Sunday), and $NIGHT_t$, which captures whether the listing end time for the same transaction was during night hours (from 6pm to 6am). We assign $WKND_t$ a value of 1 if the ending time of a remanufactured product transaction is at weekends, and 0 otherwise. We assign $NIGHT_t$ a value of 1 if the ending time of a remanufactured product j is between 6pm and 6am, and 0 otherwise. Thus, the following two null are tested:

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

Hypothesis H_{8b}: Remanufactured products listings end during night hours are associated with higher price differentials.

Return Policy: We assign the $RETURN_t$ values equal to 1 if a remanufactured product can be accepted for return by vendors, and 0 otherwise. In this case, the null under analysis 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 2 reports 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* and *NEGREP* for which the correlation index is 0.946. (The partial correlation index between these two variables calculates to 0.957.) Such 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 2, 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 2 about here

The upper panel of Table 3 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, summarised in the upper panel of Table 3, are similar to the mean and standard deviation for the unpartitioned dataset.

Insert Table 3 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 3 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 heteroscedasticity is moderate. We note that the White tests reported in Tables 4-6 actually suggest weak forms of heteroscedasticity. 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 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:

$$\begin{aligned} PD_t &= \alpha_1 + \alpha_2 \ln(POSREP_t) + \alpha_3 \ln(NEGREP_t) + \alpha_4 \ln(INCUMB_t) \\ &+ \alpha_5 (WARR_t) + \alpha_6 \ln(DEM_t) + \alpha_7 \ln(SUP_t) + \alpha_8 (MANUF_t) + \alpha_9 (WKND_t) \\ &+ \alpha_{10}(NIGHT_t) + \alpha_{11}(DURAT_t) + \alpha_{12}(RETURN_t) + \varepsilon_t \end{aligned} \tag{2}$$

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 heteroscedasticity consistent (Eicher-White) OLSR estimators. However, as highlighted in Section 5, the presence of collinearity among the 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 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 of the Unpartitioned Dataset: OLSR

The average value of price differentials in our dataset is 10 percent (see Table 3). 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 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 vendors and non manufacturer-approved vendors.

Seller reputation: Table 4 column 3 reports standard OLSR empirical estimates of Eq.(2) together with a battery of diagnostic tests for heteroscedasticity and model specification. 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 known that the latter explanatory variable is not significant at standard significance levels. Other thing 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 offset that of negative so that price differentials narrow. On the contrary, 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 stronger impact on price differentials than negative seller reputation does. It follows that sellers with poor reputation do not have to provide necessarily significant price breaks to support their selling of remanufactured products Sellers with positive reputation can benefit from wider mark-up, thus, customer policies are important key element of e-business 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, 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, as well as 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 that we do not find any support for the hypothesis H_2, H_3 and H_6 respectively.

Demand and supply proxies: Moreover, empirical results suggest that supply and demand of remanufactured products are important determinants of price differentials. In fact, we find support for the 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. Moreover, 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 proxies for remanufactured products are associated with lower price differentials. We note that an increase in demand proxies 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 the hypotheses H_4 and H_5 hold.

Listing end time/day and duration: Furthermore, 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 confirms the hypothesis H_9. We find that the availability of return policies is associated with a 46.11 percent decrease in price differentials.

In the bottom panel of Table 4 we compute a battery of diagnostic tests to investigate whether the model of Eq.(2) is correctly specified. The White and RESET statistics fail to reject the null of homoscedasticity and that there are no specification errors at standard significance levels, whereas the F-test for the null that all the explanatory variables included in the linear regression are jointly not statistically significant is soundly rejected. All in all, the above statistics suggest that the model of Eq.(2) is reasonable well specified.

Insert Table 4 about here

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

Following the empirical results set out in Table 3, 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 provide therefore further supporting evidence for the presence of multicollineary. 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 ill-conditioned information matrix. RR and MR empirical estimates of Eq.(2) are reported in the fourth and fifth column of Table 4.

More specifically, we carry 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 criteria 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 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 is used to select the optimal value of *k*. Along with the graphical inspection we make use of a number of other methods 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 parameter 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 4 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

Following our empirical results, we re-estimate Eq.(2) by using MR methods. 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 4. 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 suggest 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).

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

The empirical results set out in Table 3 suggest that price differentials of remanufactured products sold by manufacturer-approved and non manufacturer-approved vendors are characterised by two different probability distribution functions (see Fig. 1). Thus, in this Section we investigate whether the pattern of results obtained in Table 4 still holds when the entire dataset is partitioned into two subsamples (see Section 3 for detail).

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 5. 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 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 these 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 a higher price differentials (α_7 = 0.0052, *p-value*=0.01) whereas higher demand is negatively 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 the remanufactured product 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 do not play a significant effect (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 implies that a longer period of product listings increases the number of bids so that the price of remanufactured products can be potentially increased.

Insert Table 5 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, forth and fifth column of Table 6. Surprisingly, we find that the variables that used to be significant determinants of price differentials for the unpartitioned dataset as well as the partitioned dataset for non manufacturer-approved sellers become not significant when the partitioned dataset contains only manufacturer-approved vendors. Thus, the pattern of results obtained in Table 4 for the aggregate dataset is substantially driven by the trading of remanufactured products carried out by non manufacturer-approved sellers. It follows that 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 6, 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 end at weekends or during night time hours are associated with higher price differentials.

Finally, we re-estimate Eq.(2) on the second partitioned dataset by using RR and MR methods. Empirical estimates are carried out by setting the parameter k = 0.8 and by feeding the MR estimators with priors taken from the parameter estimates of Table 4. The criteria previously set out suggest values of k similar to those reported for the unpartitioned dataset. Moreover, Ridge Traces shows that the parameters α_2 and α_3 become pretty stable for values larger than 0.6. Thus, we decide to carry out RR estimates of Eq.(2) with k=0.8. 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 5 and 6. 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 empirical estimates suggests that the presence of multicollinearity does not induce any significant bias in the estimation of Eq.(2). We compute the White and RESET statistics which fail to reject the null of homoscedasticity and no specification errors at standard significance levels. The F-test soundly rejects the null that the explanatory variables are jointly not statistically significant. All in all, the above diagnostic tests suggest that the model of Eq.(2) is reasonably well specified when applied to the two partitioned datasets.

Insert Table 6 about here

7.5. Robustness Checks

We carry out a number of robustness checks for the empirical estimates reported in Table 4. We initially re-estimate 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. We then re-estimate Eq.(2) on a restricted dataset in which $POSREP_t$ assumes values within its mean plus/minus three times its standard deviation. In this case the number of observations available reduces 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. Finally, we carry out a final robustness check by replacing in Eq.(2) the separate positive and negative reputation measures with a single reputation score calculated as the difference between the two. The above empirical exercises are then repeated for the two partitioned datasets. All in all, the empirical results suggest that the sign, magnitude and statistical significance of the estimated parameters are by large consistent with those set out in Tables from 4 to 6. (Please note these 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 Square Regression, Ridge Regression (RR) method to deal with the statistical issue of collinearity among the explanatory variables, and Mixed Regression (MR) method. Our empirical results suggested seller positive reputation, the length of warranties, the proxies of demand and supply of remanufactured products, the duration and end day of remanufactured product listings are important market determinants of price differentials. More specifically, we found seller identity (i.e. manufacturer-approved or non manufacturer-approved vendors) played an important role as our empirical results were predominantly driven by transactions carried out by non manufacturer-approved vendors. We can conclude price differentials of remanufactured products listed by manufacturer-approved sellers must be driven by a different set of market 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.

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Table 1 Subcategories of Electronics product category

Subcategories of *Electronics*			
Index	Subcategory Title	Index	Subcategory Title
1	Digital cameras	14	Headsets
2	Camcorders	15	Chargers & Docks
3	Camera & Photo Accessories	16	Televisions
4	Lenses & Filters	17	DVD, Blue ray & home cinema
5	Digital Photo Frames	18	TV Reception & Set-Top Boxes
6	Laptops & netbooks	19	TV & Home Audio Accessories
7	Desktops & All-in-Ones	20	iPods & MP3 players
8	iPads, Tablets & eReaders	21	Headphones
9	Printers, Scanners & Supplies	22	Home Audio & HiFi Separates
10	Home networking	23	Consoles
11	Computer Components & Parts	24	Accessories
12	Mobiles & smart phones	25	Controllers
13	Home Phones & Accessories	26	Headsets

Table 2 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 3 Price differentials: basic statistics

	Price Differentials Include both manufacturer-approved and non manufacturer-approved vendors	**Price Differentials** (*MANUFt* = 1) Only include manufacturer-approved vendors	**Price Differentials** (*MANUFt* = 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 is in parenthesis.
3. Mann-Whitney Test for the null of equality in median. P-value is in parenthesis.
4. Levene test for the null of equality in variance. P-value is in parenthesis.
5. Barnett & Eisen (1982) test for the null of equality in distribution. P-value is in parenthesis.
6. Kolmogorov-Smirnov Test for the null of equality in distribution. P-value is in parenthesis.
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 4 Linear regressions for log transformation of price differentials

Explanatory Variable	**Parameter**	**Log-Normal Regression (SD in parenthesis)**	**Ridge Regression (SD in parenthesis)**	**Mixed regression (SD in parenthesis)**
POSREP (ln)	α_2	-0.028**	-0.028**	-0.028**
		(0.0128)	(0.0128)	(0.0128)
NEGREP (ln)	α_3	0.0167	0.0166	0.0167
		(0.0125)	(0.0125)	(0.0125)
INCUMB (ln)	α_4	-0.0086	-0.0087	-0.0086
		(0.0231)	(0.0231)	(0.0231)
WARR	α_5	0.0005	0.0005	0.0005
		(0.0036)	(0.0036)	(0.0036)
DEM (ln)	α_6	-0.0001*	-0.0001*	-0.0001*
		(0.00006)	(0.00006)	(0.00006)
SUP (ln)	α_7	0.0021*	0.0021*	0.0021*
		(0.0012)	(0.0012)	(0.0012)
MANUF	α_8	-0.0272	-0.0272	-0.0272
		(0.0336)	(0.0336)	(0.0336)
WKND	α_9	0.1158**	0.1157**	0.1157**
		(0.0451)	(0.0451)	(0.0450)
NIGHT	α_{10}	0.0277	0.0277	0.0277
		(0.0261)	(0.0261)	(0.0261)
DURAT	α_{11}	-0.0021	-0.0021	-0.0021
		(0.0016)	(0.0016)	(0.0016)
RETURN	α_{12}	-0.0893**	-0.0894**	-0.0893**
		(0.0393)	(0.0393)	(0.0393)
Intercept	α_1	0.4234***	0.4234***	0.4244***
		(0.1471)	(0.1470)	(0.1471)
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)
RESET Test[3]		2.396	2.398	2.393
		(0.091)	(0.092)	(0.092)
R^2		0.166	0.166	0.166
Observations		917	917	917

Notes: Dependent variable defined as -ln(1-PD_t). * (**) [***] Significant at 10 (5) [1] percent. Ridge regression (RR) estimated with parameter *k*=0.8. Mixed regression (MR) 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 is in parenthesis.

2 White heteroscedasticity test for the null of homoscedasticity. P-value is in parenthesis.

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

Table 5 Linear regressions for log transformation of price differentials ($MANUF_t$=0)

Explanatory Variable	Parameter	Log-Normal Regression (SD in parenthesis)	Ridge Regression (SD in parenthesis)	Mixed regression (SD in parenthesis)
POSREP (ln)	α_2	-0.0395**	-0.0394**	-0.0395**
		(0.0197)	(0.0196)	(0.0196)
NEGREP (ln)	α_3	0.0179	0.0179	0.0179
		(0.0206)	(0.0206)	(0.0206)
INCUMB (ln)	α_4	-0.0017	-0.0018	-0.0018
		(0.0329)	(0.0328)	(0.0329)
WARR	α_5	-0.0078**	-0.0078**	-0.0078**
		(0.0035)	(0.0035)	(0.0035)
DEM (ln)	α_6	-0.0002**	-0.0002**	-0.0018**
		(0.00009)	(0.00009)	(0.00009)
SUP (ln)	α_7	0.0052***	0.0051***	0.0052***
		(0.0019)	(0.0019)	(0.0019)
MANUF	α_8	-	-	-
		(-)	(-)	(-)
WKND	α_9	0.1078*	0.1078*	0.1079*
		(0.0581)	(0.0581)	(0.0579)
NIGHT	α_{10}	-0.0205	-0.0205	-0.0204
		(0.0432)	(0.0434)	(0.0431)
DURAT	α_{11}	-0.0079***	-0.0079***	-0.0078***
		(0.0029)	(0.0030)	(0.0030)
RETURN	α_{12}	-0.0632	-0.0633	-0.0632
		(0.0594)	(0.0594)	(0.0595)
Intercept	α_1	0.5002**	0.5002**	0.5002**
		(0.2184)	(0.2181)	(0.2183)
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)
R^2		0.21	0.21	0.21
Observations		436	436	436

Notes: Dependent variable defined as -ln(1-PD_t). * (**) [***] Significant at 10 (5) [1] percent. Ridge regression (RR) estimated with parameter k=0.8. Mixed regression (MR) estimated with priors taken from empirical estimates of Table 4.

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

2 White heteroscedasticity test for the null of homoscedasticity. P-value is in parenthesis.

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

Table 6 Linear regressions for log transformation of price differentials ($MANUF_t$=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)
NEGREP (ln)	α_3	0.0121	0.0121	0.0121
		(0.0159)	(0.0159)	(0.0160)
INCUMB (ln)	α_4	-0.0133	-0.0133	-0.0133
		(0.0315)	(0.0315)	(0.0315)
WARR	α_5	0.0036	0.0036	0.0036
		(0.0056)	(0.0056)	(0.0056)
DEM (ln)	α_6	-0.00006	-0.00006	-0.00006
		(0.0001)	(0.0001)	(0.0001)
SUP (ln)	α_7	0.0015	0.0014	0.0015
		(0.0016)	(0.0016)	(0.0019)
MANUF	α_8	-	-	-
		(-)	(-)	(-)
WKND	α_9	0.129*	0.129*	0.1289*
		(0.0688)	(0.0688)	(0.0687)
NIGHT	α_{10}	0.0606*	0.0606*	0.0606*
		(0.0348)	(0.0348)	(0.0347)
DURAT	α_{11}	-0.001	-0.0009	-0.001
		(0.0016)	(0.0016)	(0.0016)
RETURN	α_{12}	-0.1059**	-0.1059**	-0.1059**
		(0.0524)	(0.0524)	(0.0524)
Intercept	α_1	0.3513*	0.3511*	0.3513*
		(0.1909)	(0.1909)	(0.1908)
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)
R^2		0.144	0.144	0.144
Observations		481	481	481

Notes: Dependent variable defined as -ln(1-PD_t). * (**) [***] Significant at 10 (5) [1] percent. Ridge regression (RR) estimated with parameter k=0.8. Mixed regression (MR) estimated with priors taken from empirical estimates of Table 4.

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

2 White heteroscedasticity test for the null of homoscedasticity. P-value is in parenthesis.

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

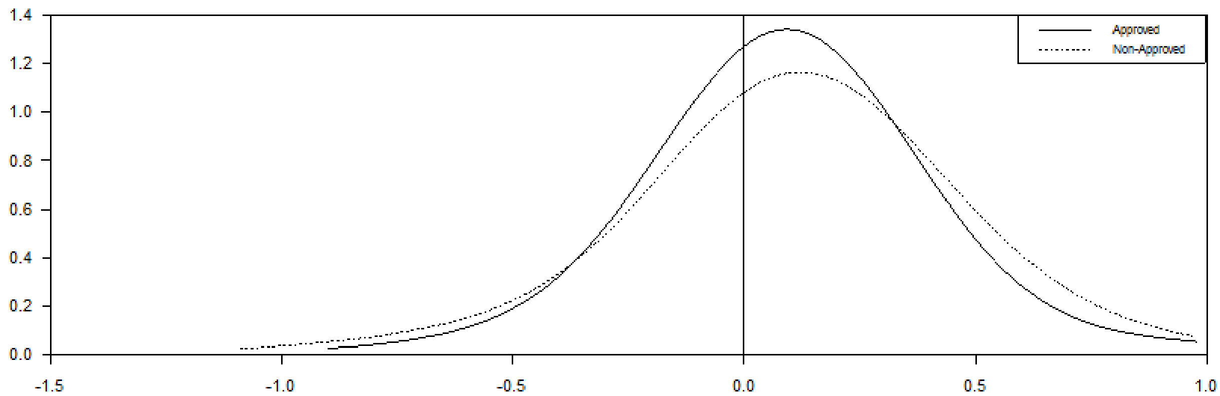

Figure 1 Empirical probability distribution functions of price differentials for manufacturer-approved sellers (solid line) and non manufacturer-approved sellers (dotted line)

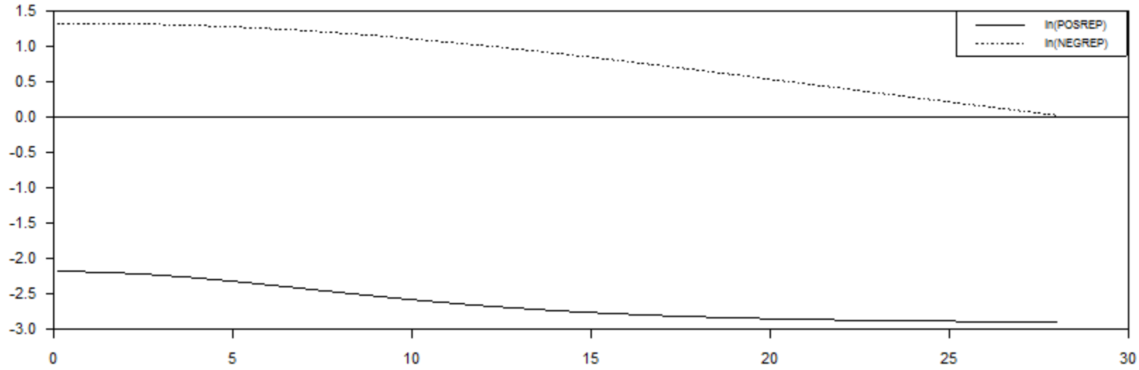

Figure 2 Ridge Trace for the t-ratios of parameters α_2 (ln(*POSREP$_t$*) solid line) and α_3 (ln(*NEGREP$_t$*) dotted line) estimated on the unpartitioned dataset. Values of the statistics reported on the vertical axis and values of *k* on the horizontal axis.