Market Structure, Reputation, and the Value of Quality Certification*

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This draft: May 2013

Abstract

Quality certification programs are used to improve consumers' ability to identify high-quality products or sellers in markets with information asymmetries. Using data from eBay UK's online marketplace, we study how certification's benefits vary with market- and seller-level attributes, exploiting quasi-experimental variation in sellers' certification status. The positive effects of eBay's "top rated seller" certification are stronger for categories with relatively few other certified sellers, in more competitive markets, and for sellers with shorter records of past performance. These findings indicate certification provides its greatest value when certification is rare, the product space is crowded, and for sellers lacking established reputations.

JEL Codes: D82, L15, L25, L86
Key words: information asymmetry, quality certification, market structure, eCommerce

* We thank eBay, and in particular Brad Matthews, Jana Moles, Jana Honnerova, Irene Garcia Sacedon, and Vasanth Yenegalla. Additionally, we thank seminar participants at Arizona State University, the Federal Trade Commission, UCLA, the University of North Carolina – Charlotte, the University of Michigan, and the University of Minnesota for their helpful comments.

1. Introduction

It is well-established that quality certification can reduce information asymmetries between buyers and sellers, and thus may remedy “lemons” problems that cause exchange to break down (Akerlof 1970, Viscusi 1978).[1] As a result, quality certifications are a common feature in a range of markets, including consumer retail, firm-to-firm trade, specialty services like medical treatment and auto repair, and labor markets. The ubiquity of such “expert” guidance has spawned a large related empirical literature (surveyed by Dranove and Jin 2010) that has provided many useful insights on the efficacy and attributes of certification mechanisms. At the same time, studies in this area generally feature a close examination of how quality certification affects trade in a single market, where the competitive environment and information context is held fixed. This makes it difficult to answer a host of important questions, such as: How does certification’s value depend on the number of competing products nearby on store shelves or webpages? How might certification’s value differ between industries with a high scope for seller opportunism – as in automotive services – versus those with little quality uncertainty – like the market for toasters? How might the certification’s quality threshold affect its value? And how do alternative reputational signals like crowd-sourced feedback affect the value of certification?

In this paper, we extend the existing literature by exploring how the impact of a single quality certification institution varies across a range of markets that differ in competitiveness and underlying quality uncertainty, and also across sellers with different reputations. Specifically, we study empirically the effects of a seller-quality certification program on the UK platform of eBay’s internet marketplace. Our data span all eBay product categories, which differ substantially in market concentration and levels of quality uncertainty, and involve sellers with widely differing levels of past transactions. Despite this significant heterogeneity in market attributes, all eBay sellers are evaluated for eBay’s Top-Rated Seller (eTRS) certification based on the same quality criteria, which affords a unique opportunity to assess how market conditions affect the value of quality certification, holding the certification criteria constant.

The size and richness of our dataset allows us to identify the benefits of certification in near-identical listings for a given seller. Specifically, we observe the universe of listings and sales for eBay UK sellers who received eBay’s Top-Rated Seller certification badge at some

[1] The literature has considered a wide variety of mechanisms for individual firms to signal quality and build consumers’ trust, e.g. Milgrom and Roberts (1986), Grossman (1981), Klein and Leffler (1981). Third parties can also act to monitor and rate firm’s quality and performance, e.g. Lizzeri (1999).

point during the first year of the eTRS program. From this dataset of over 100 million product listings, we assemble the set of matched listings where the same seller offers the same product (based on exact match of title and subtitle) but with some variation in listing details, including whether the seller possesses the eTRS badge at the time of listing. Institutional features of the eTRS program – especially the fact that sellers gain and lose eTRS certification abruptly – allow us to cleanly identify the impact of quality certification on demand. Thus, we avoid potential correlation between unobserved firm quality and certification status, which can cause endogeneity problems in studies of purely observational data. Our data include information about the number of times a listing is served to consumers as a search result and also how frequently a listing's detailed webpage is displayed. This enables us to examine (and also control for) the impact of certification on the placement of sellers' items within search results and the frequency of click-throughs to the listings themselves. We conduct our empirical analysis on a matched sample of 16 million observations in over 8,000 eBay product categories, with sellers who vary substantially in their public histories of past transactions.

Ex ante, the effect of market attributes on the value of certification is ambiguous. In a market where most sellers are quality-certified, the absence of certification could convey a very negative signal about (relative) unobserved quality, in which case the certification premium would be increasing in eTRS prevalence. Alternatively, if certification is rare, consumers may interpret this as a sign of significant quality concerns in the marketplace, thus increasing certification's value. There is similar ambiguity in the case of market concentration. Certification may be an increasingly useful means of "vertical" differentiation as horizontal product market competition intensifies; alternatively consumers may view the additional benefits to a particular product's certification as having a fixed value, unrelated to the number of other products in a category. The findings we present will offer some guidance in assessing which of these effects dominate empirically. To provide a conceptual underpinning for the empirical regularities we observe, we present a simple theoretical model based on unobserved seller quality, imperfect customer feedback, and the assumption that eBay has an information advantage relative to buyers. The model highlights an intuitive mechanism relating eTRS prevalence to the certification premium: In product categories with lower average seller reliability, fewer firms obtain certification and the value of certification is thus greater since it carries more informational content. A simple extension relates category concentration to the certification premium. Modeling competition as horizontal product differentiation, we show that eTRS status will have a greater impact on sales probability in more competitive categories (holding price constant), since vertical differentiation is more valuable in the face of intense product market competition. The model also generates the straightforward prediction that the value of outside certification becomes less important (for high-quality sellers) as the seller accumulates customer feedback.

Our analysis begins by documenting that gaining eTRS certification is associated with a significant increase in demand. We find that certification increases by 7% the probability that a given seller's fixed-price listing ends successfully with a sale. When combined with price sensitivity estimates that come from variation in sellers' posted prices, this implies that, holding the seller and listing title fixed, consumers will pay about 7% more for eTRS-badged items. For an item with the median price (£14) in our matched data, a price difference of £0.94 will generate equal sale probabilities between badged and unbadged items. Our estimates suggest that, in aggregate, sellers who gained eTRS certification earned an additional £26.8 million in the year following introduction of the eTRS program, or roughly £1,110 per certified seller.

We then proceed to analyze our questions of principal theoretical interest, i.e., how market and seller attributes affect the value of certification. First, we show that in categories with few other badged listings – where we argue that concerns of unobserved seller quality are most prevalent – the impact of certification is much greater. For listings in categories with the lowest quartile of eTRS listing frequency, certification's impact is nearly three times as large as in markets with the highest frequency of eTRS listings (11% vs. 4%). At least some of these increased sales come through "business stealing" – we also show that an increase in eTRS prevalence negatively affects the sales of sellers whose eTRS status (as either certified or uncertified) is held fixed. Second, we also find that the eTRS badge has greater effects in markets that are less concentrated, measured by category-level Herfindahl indices, consistent with the view that vertical differentiation is more valuable when product market competition is more intense. Finally, we document the link between seller-level reputation and the value of certification. In the eBay marketplace, a seller's record of prior transactions is summarized as a publicly-observed cumulative feedback score. Consistent with feedback serving as a substitute for eBay's own quality certification, we find that sellers with scores in the lowest quartile of those in the matched sample have an 8% increase in sale probability from the badge, while those in the highest quartile have a badge effect of 5%. Thus, certification's impact is amplified for sellers with relatively few past sales transactions, who have not yet had the opportunity to signal their reliability to prospective buyers.

Collectively, the findings highlight the importance of considering the characteristics of a market or industry in assessing the likely effects of quality certification. In particular, we show that the value of certification depends on the prevalence of other certified sellers, the competitive relationship among firms, and the availability of alternative reputational mechanisms. We emphasize that while eBay serves as a particularly convenient context for studying these issues, the questions we address have implications for understanding the role of certification in a wide range of markets.

We contribute to a literature that has previously focused on the impact of quality certification in individual markets. Jin and Leslie (2003), for example, demonstrate that the introduction of restaurant hygiene report cards in Los Angeles resulted in consumers sorting toward cleaner establishments and a reduction in the incidence of food-related illnesses. Similarly, Wimmer and Chezum (2003) find that certified racehorses sell for higher prices and go on to have better racing careers than uncertified horses. Improved sorting can allow the benefits of quality certification to extend to low-quality products, as Tadelis and Zettelmeyer (2011) describe in a field experiment looking at a used car auction market. Ramanarayanan and Snyder (2012) examine a public grading system for dialysis centers, and show that centers with low grades serve fewer well-informed patients, and that these low grades motivate centers to improve performance. In the same spirit as some of our findings, Xiao (2010) shows that certification has little impact on demand in the market for childcare services if alternative quality information is already provided by firms.[2] To our knowledge, we are the first to examine how differences in market-level attributes affect the consumer responses to certification; our work can

[2] In some cases, firms' pursuit of quality certification can have unintended or perverse effects. Dranove et al. (2003) show that hospitals may decline treatment to severely sick patients in order to avoid risking poor grades in New York's hospital "report card" program, while Forbes, Lederman, and Tombe (2012) explore the incentives of airlines to manipulate arrival times to sustain records of on-time arrivals. In all of these studies (and in our own), the certifying organization is a government body or market-maker seeking to promote trade by providing information that the firms will not or cannot credibly provide independently. As discussed in Jin and Leslie (2003), selection effects in firms' reporting decisions may undermine the benefits of voluntary information disclosure. There is also a rich literature on self-interested third-party intermediaries (e.g. Moodys) that provide quality information about firms, while also perhaps pursuing their own profit maximizing objectives or seeking to please the market participants (often firms) that underwrite their existence (e.g., Becker and Millbourn 2011).

help to guide our understanding of where certification will be most valued by firms and consumers.

More broadly, our paper is a part of a growing literature on the role of quality-assurance mechanisms in stimulating trade. Much of this work has been motivated by the growing importance of e-commerce and has been enabled by the increasing ease with which detailed information may be collected from online marketplaces. Lewis (2011) analyzes used car listings on eBay, and finds that sellers' voluntary provision of quality information helps alleviate adverse selection. eBay's official reputation mechanisms, specifically whether a seller opens a "store" on the site or qualifies for (the now defunct) PowerSeller certification, also stimulate trade, as Saeedi (2012) finds in a study of the iPod market. eBay sellers may also signal trustworthiness through their charity commitments, at least until they develop the performance track records necessary to indicate reliability (Elfenbein, Fisman, and McManus 2012). Not all quality-assurance programs are successful, however, as Roberts (2011) reports that a warranty program for online tractor sales is unable to substitute for more traditional measures of seller reputation. Outside of online markets, Jin and Leslie (2009) consider how the reputational incentives of chain membership and the possibility for informational spill-overs affect hygiene practices in Los Angeles restaurants. Similarly, Luca (2011) examines the impact of changes in on-line Yelp ratings on restaurant industry sales and finds minimal impact on the sales of chain restaurants.

The remainder of the paper is organized as follows. In section 2, we describe the features of the eBay UK platform and the Top-Rated Seller program. In section 3, we outline the main assumptions and predictions of an illustrative theoretical model, which we develop fully in the Appendix. In section 4, we discuss the construction and characteristics of the data. Section 5 presents the empirical analysis, and section 6 concludes.

2. Background and setting

A. eBay's United Kingdom auction platform

Founded in the United States in 1995, eBay has emerged as the world's largest online marketplace. In 2011, the site claimed over 100 million users globally, with goods valued at over $68 billion traded on the eBay platform.[3] A United Kingdom site, www.ebay.co.uk, was launched in 1999 and has become eBay's second most active marketplace, after the US-based

[3] These figures come from www.ebayinc.com/who [accessed 7/25/2012].

site. According to the web information provider Alexa, ebay.co.uk's global web traffic rank is 85, and sixth within the UK; by comparison www.ebay.com, is ranked 23 worldwide and seventh in the US.[4] The main features of eBay's UK platform mimic those of the US-based platform, which have been described extensively in other studies (e.g., Bajari and Hortascu 2004, Hauser and Wooders 2006, Lucking-Reiley et al. 2007, Elfenbein and McManus 2010). There are, however, several noteworthy differences. First, prices for items on the site are listed in pounds rather than dollars. Second, sellers are mainly UK-based with a relatively small proportion coming from other European countries and also China and Hong Kong. Third, shipping prices are generally for standard economy shipping through the Royal Mail within the UK. Finally, a larger fraction of items on the UK platform are listed for sale at fixed prices (instead of auctions) than on the US site[5] and a greater proportion of items are listed by professional sellers.

B. The Top-Rated Seller (eTRS) program

Buyers on eBay purchase products they cannot inspect from sellers with whom they cannot have face-to-face communication, and whom they trust to deliver the product after payment is received. As a result, this marketplace is vulnerable to misrepresentation of products by sellers, and service problems *ex post* (e.g., packaging the product in such a way that it might be damaged in shipping, shipping the product late, etc.), not to mention outright fraud. Easy entry (and exit) from these marketplaces by sellers exacerbates this set of problems (Brown and Morgan 2006).

Since its founding, eBay has relied on a feedback system to allow buyers and sellers to establish reputations for following eBay norms and being reliable transaction partners. When an eBay user is the seller in a transaction, his eBay feedback score increases by 1 if the transaction's buyer provides positive feedback; conversely, the feedback score is reduced by 1 if the buyer leaves negative feedback. When an eBay user acts as buyer in a transaction, he may receive positive feedback from the seller but not negative feedback. Webpages of products listed for sale on eBay include a display of the seller's feedback score and his fraction of positive feedback. A potential buyer also has the option of visiting a separate webpage to examine feedback ratings and comments the seller received on items sold in the previous 90 days.

[4] Source: http://www.alexa.com/siteinfo/ebay.co.uk [accessed 10/9/2012].

[5] For example, in the digital camera category on October 9, 2012, 98 percent of 9,634 items for sale in the UK were listed at a fixed price vs. 80 percent of 55,241 items on the US site. For new digital cameras, the figures are 99.7 and 95.4 percent, respectively. See Einav et al (2013) for a discussion of the decline of auctions on eBay.

Although this feedback system has been effective in supporting trade at an aggregate level, researchers have shown that the feedback system is vulnerable to manipulation (see Bolton et al. 2012; Brown and Morgan 2006; Dini and Spagnolo 2009; and others). To augment the feedback and reputation system, eBay introduced Detailed Seller Ratings (DSRs) in 2007 and the eBay Top-Rated Seller (eTRS) program in 2009.[6] Under the DSR program, in addition to providing positive or negative feedback and comments, buyers have been asked to rate sellers following a transaction along four dimensions: Was the item received as described by the seller? Was the seller's communication effective? Was the product shipped in a timely manner? And were the shipping and handling charges reasonable? Each of these questions is rated on a five-point scale. If the buyer chooses to do so, he can find the average scores along these dimensions displayed in graphical form as well as the number of ratings on which the average is based by clicking through to the seller's profile page (the link to this page is provided on each product listing page).

To become a Top-Rated Seller in the UK when the program started in 2009, sellers had to meet a number of requirements pertaining to time the account had been active, transaction volume, percentage of positive feedback, and DSR ratings.[7] Specifically, Top-Rated Sellers needed to have at least 100 transactions or £2000 of sales in the prior year with UK (or Irish) buyers, a positive feedback rating of at least 98%, and minimum average DSR scores of 4.6 out of 5. Furthermore, sellers could have no more than 0.5% or two instances of DSR ratings of 1 or 2 in the prior three months (if 400 or more transactions) or in the prior twelve months (if fewer than 400 transactions in the past 3 months). Additionally, Top-Rated Sellers had to be registered as businesses on eBay, and had to include a comprehensive returns policy within each listing.

While a seller's average DSR scores are publicly visible, eBay has an informational advantage relative to consumers in its ability to track instances in which the seller received very low DSR ratings on individual transactions. Many sellers on the eBay marketplace may have similarly high DSR averages or cumulative feedback scores, so the eTRS badge is essentially a statement about the (low) probability of a certified seller providing severely unsatisfactory

[6] Prior to the eTRS program, eBay reported a seller's PowerSeller designation (none, bronze, silver, gold, platinum, or titanium) as a quality signal. PowerSeller levels were based largely on sales volume, however, and eBay designed eTRS certification to be more informative about per-transaction expected quality.

[7] The qualifications necessary for the eTRS badge have evolved since the program was introduced, and now includes limits on the number of open "buyer protection cases."

service. In the absence of the eTRS badge it would not be easy for consumers to predict whether a seller would meet the eTRS certification standard. Correlation between DSR scores and eTRS status is positive but small (ranging from 0.12 to 0.15), and likewise for seller feedback.

Top-Rated Seller status is assessed monthly. On the 20th day of each month, eBay evaluates seller performance over the prior three months (or twelve months for sellers with fewer than 400 transactions). Changes in eTRS status are effective at the time of this assessment, and open listings are updated dynamically to reflect the current seller status. Thus, if a seller's performance at the beginning of a calendar month pushes her performance metrics above the eTRS threshold, she will receive a badge when eBay makes its next monthly assessment.[8] Similarly, if a seller's slipping performance in a given month leads her to fall below the eTRS threshold she would keep her badge until the next assessment. A seller's eTRS status applies across all categories in which she posts listings, regardless of the extent of the seller's performance within a particular category.

The first eTRS badges appeared on seller listings in the UK in late September 2009. During the period we study, the eTRS badge was a small ribbon with the words "Top Rated Seller." Beginning one month into the program, the badge was also displayed next to the product title on the search results page (see Figure 1). This enabled buyers to distinguish between listings sold by eTRS and non-eTRS sellers prior to viewing pages with detailed product descriptions and purchase options. The eTRS badge was also displayed alongside other seller information on the product description pages (see Figure 2). Finally, the eTRS badge appeared on the seller information page (see Figure 3).

In addition to displaying the eTRS badge on the results and listings pages, eTRS sellers also received other benefits. In particular, eTRS sellers received discounts (up to 20%) on final value fees paid to eBay, and as of late November 2009 improved search standing for listings in Best Match search results.[9] The Best Match search results were delivered through a proprietary and ever-evolving algorithm. For many users, Best Match was the default method through which search results were displayed, but users could also sort results by time, price, or distance. In our

[8] We encountered in the data only a small number of off-schedule adjustments to sellers' eTRS status, and we account for these changes in the same way we treat standard eTRS updates. Most transitions in and out of eTRS certification occur on the 20th of the month.

[9] Identical fee discounts were also provided to high-volume sellers whose performance was below the eTRS threshold.

empirical analysis, we will thus take considerable care in accounting for a particular listing's visibility in search results.

3. Illustrative model and empirical predictions

Before proceeding to the data, we discuss the theoretical framework we will use to organize and interpret our analysis. We focus on the intuitions gleaned from a more formal modeling exercise, which we include in the Appendix. As we noted in the introduction, the predicted relationships between market attributes and the value of certification are not clear. The purpose of this section is to show that the effects that dominate in our empirical analyses can easily be reconciled with standard models of competition augmented by unobserved quality.

We are interested, broadly speaking, in how seller and market characteristics affect consumer response to quality certification. In the case of intensity of product market competition, we rely on prior art to frame our analysis. The first model we describe in this section encapsulates the intuition that vertical differentiation is more valuable in circumstances where firms are more similar to each other in their horizontal attributes. Specifically, consider a standard Salop (1979) circular city model where evenly-spaced firms sell to uniformly distributed consumers with binary demand. The true quality of seller i is captured by the parameter α_i, representing the likelihood that a seller offers an error-free transaction ($\alpha_i < 1$). Suppose, for simplicity, that seller types are either high (H) or low (L), with $\alpha_H > \alpha_L$. Absent feedback or certification, all sellers are perceived as having reliability $E(\alpha)$, reflecting the prevalence of reliability levels in the overall population of sellers. In this framework, quality certification of seller i informs consumers that $\alpha_i = \alpha_H$. Holding prices fixed (as we are able to do with our quasi-experimental data), quality certification will induce an increase in quantity demanded that is independent of initial market share. This implies larger proportional changes to market shares when initial shares are smaller, as is the case when N is greater. In summary: *A seller experiences a larger percentage increase in sales due to certification when the seller is in a more competitive market.*

In the second part of the Appendix, we provide a discussion of the construction of $E(\alpha_i)$ based on information about sellers that accumulates over time. We presume consumers can observe public feedback, quality certification, and a measure of how "risky" a product market might be; we collect these pieces of information in Ω_i for seller i. We specify a simple two-period model to highlight an intuitive set of predictions that we analyze in the data. We retain the assumption that sellers differ in their unobserved quality – either high or low. Sellers operate in a single category, and the distribution of seller quality varies across product categories (markets). This variability may result, for example, from product attributes such as *ex ante* verifiability of product quality and/or the likelihood of breakage in delivery. After each transaction, a buyer has the opportunity to provide publicly observable feedback. Prior to any transactions, eBay also may observe, with some probability, a perfectly informative signal of seller quality. We assume that, on the basis of this independent signal, a seller is given eTRS status if eBay learns that the seller is of high quality. Consumers use Bayes' rule to form beliefs about $E(\alpha_i|\Omega_i)$ based on the feedback a seller has received combined with the seller's eTRS status.

Our spare model delivers two further predictions that relate seller and market attributes to the value of certification: (1) *Certification's value is decreasing in the fraction of sellers in an industry that are quality-certified,* and (2) *The value of certification diminishes with the accumulation of buyer feedback, since the two serve as substitutes for one another*. The former prediction is driven by the fact that since average seller quality is lower when certification is rare, buyers update more strongly in response to certification. It is worth reiterating that in practice the eTRS requirements are the same regardless of the ease or difficulty of selling in a particular category, so it is plausible that differences in the category-level prevalence of certification are the result of differences in sellers' unobserved ability to meet eBay's eTRS standards while serving a particular market.

4. The data

A. Sample period and data extract

We examine a large data extract from eBay's UK platform. The extract includes data on individual listings that conclude between September 29, 2009 (the eTRS program's first day) and October 31 2010. For 44,658 sellers who ever attain eTRS status during the program's first year, we observe their full collection of listings during the sample period. These "eTRS sellers" account for 113 million listings in the data extract. We also observe all listings by an additional 1,982 sellers who approach but do not achieve eTRS status during the sample period; this accounts for 7 million listings. Finally, eBay provided a 10% sample of listings from the entire UK marketplace, excluding those sellers for which we have complete data. The 10% sample contains 33 million listings from 2.2 million distinct sellers. The relative sizes of the extract's components implies that the UK marketplace hosted approximately 450 million listings during the 13 month sample period, with 25% coming from sellers who held eTRS status at some point during this time.

The listing data provide information on a product's seller and the product itself; each listing's selling format (e.g. true auction or fixed price); the number of units available and sold; listing details such as start date, end date, number of photos displayed, and shipping fees; the fixed price or auction starting price, as appropriate; and for auctions the data provide the number of bids, selling price, and maximum bid value. We also observe the number of times a listing was shown to consumers (an "impression") as part of a list of search results within a product category or following a consumer's query, and the number of times the listing's full webpage was viewed by a consumer (a "click-through"). Seller and listing characteristics, including the presence of an eTRS badge, affect eBay's algorithm for serving search results to consumers, so controlling for the numbers of impressions and views is important for separating the informational effect of the eTRS badge from its effect on a listing's visibility in buyer searches.

We supplement the listing data with a panel of seller-level data. For the sellers with complete listing data, we observe their complete eTRS badge history. We see detailed seller ratings (DSRs) and feedback scores monthly. Finally, we observe the annual and quarterly summaries of transactions and revenue that eBay uses to evaluate a seller's eTRS status, and the permanent seller characteristics of "age" (time since first transaction on eBay) and home country (90% are British, with the remainder primarily from China and Hong Kong).

We observe each item's location in eBay's hierarchy of product categories, and identify a product's market based on its eBay "leaf category," which is the most specific product classification in the eBay hierarchy. The listings in the data extract are drawn from over 8,000 distinct leaf categories, which themselves are members in one of 38 top-level categories. For example, within the top-level category "Consumer Electronics," there is a leaf category for the 4GB Apple iPod Mini model. The variety of products within a leaf category is determined, in part, by the eBay market thickness for a class of products, and there will be variation across categories in the substitutability of products that are grouped together.

We use the full listing data, the seller characteristics, and the leaf category codes to create several panels of market-level data. The panels summarize weekly activity on the eBay UK marketplace. Within each week and leaf category, we count the number of listing-days associated with each active seller, the number of units sold, revenue collected, and the seller's eTRS badge status. We then aggregate these data within a market-week, and calculate market concentration measures like Herfindahl-Hirschman Indices (HHIs) and shares of all listings, sales, and revenue that originate with eTRS-badged sellers.[10] We assume that a category's market structure and eTRS share are uncorrelated with unobserved factors that might drive category-level differences in consumers' responses to the eTRS badge.

B. Matching procedure and sample characteristics

From the data extract we assemble two types of "quasi-experiments," which we label "ST" (seller-title) and "STP" (seller-title-price) matches, respectively. An ST-match consists of a group of two or more listings from a single seller that use the same title, subtitle, and selling format (e.g. fixed price).[11] An STP-match is a group of items listed by the same seller that use the same title, subtitle, selling format, *and* posted price or start price, as appropriate based on selling format. We have used this approach in our earlier work (Elfenbein, Fisman, and McManus 2012), as have Einav et al. (2011) in other research using data from eBay's US platform. A large proportion of eBay listings from high volume sellers can be matched in this way. Among the 113 million listings in the data extract from eTRS sellers, over 100 million can be included in a match. There are many instances where a seller's eTRS status differs between listings in a match as a result of an individual seller having gained or lost eTRS status. Under the assumption that this within-match variation in eTRS status is exogenous with respect to demand, product, and seller characteristics, the differences in eTRS status provide an opportunity to credibly estimate its impact on demand. This is plausible in our setting because small changes in seller attributes produce a discrete change in eTRS status around the eTRS eligibility threshold.

Starting with the full collection of 100 million matched listings, we exclude 38 million auction-style listings from our analysis, since these listings account for considerably less trade on

[10] We combine the 10% and 100% samples of sellers' listings by weighting the latter group's listings and transactions by 0.1 while calculating market activity summaries.

[11] eBay identifies three major selling formats: "fixed price," "store fixed price," and "auction." In our discussion we use the term "fixed price" to describe the first two selling formats, although we separate these formats in creating the matches. This implies that format-specific differences in average listing outcomes are picked up by the match fixed effects we introduce below.

eBay UK than fixed price offerings.[12] We then drop 18 million fixed-price matches with an average posted price below £4.95 or above £500; virtually all dropped listings have prices below the lower threshold. About 17% of the remaining listings are eliminated because the seller did not change eTRS status during the sample period (most often because the seller received certification immediately and never lost it). We also drop a small share of additional observations because of missing data, unusually large quantities offered within single listings, or other irregularities. Ultimately, we are left with a sample of approximately 31 million listings. Within these listings, we restrict our attention to the 16.6 million listings that have within-match variation in the quantity of items sold (i.e., whether an item sold in the case of single-item listings), since these listings are most important to our empirical analysis.

In Table 1 we summarize the listing-level characteristics of the final set of ST matches. Out of 16.6 million listings, 52% have an eTRS badge when the listing ends and 27% finish with the sale of one or more units of the seller's product. Many fixed-price listings feature multiple units. For these listings our data provide the quantities available and sold. At the data medians, listings are active for 10 days, include one photo of the item for sale, and have a shipping fee of £1.50. Listings typically appear in categories that are fairly competitive as measured through HHI, which is not surprising given the ease of becoming an eBay seller; however, there is wide variation in HHI across categories. For the sample of matched listings, the average category-level eTRS share is 24%. The mean price is £26.29 (median £13.99) for successful transactions, which is slightly below the average posted price among the matched listings. The average number of units sold per listing (0.68) is greater than the overall success rate due to successful sales of multiple units from a single listing.

Our sample of 16.6 million fixed-price listings contains data from 24,115 sellers, whose characteristics are summarized at the bottom of Table 1. The median seller has 123 listings across 12 ST matches. The mean and median feedback scores are 4283 and 1574, respectively, indicating that this group of sellers is well-established on the eBay platform. The median seller has 200 successful transactions per quarter and £3450 in revenue; the means for these variables are about three times the median values. Finally, despite their size, the sellers generally have a small share of the total number of listings or quantity within each item's category.

[12] The fixed price listings captured by our matching procedure result in transactions that have total revenue value that is six times as large as the value of the matched auction listings.

5. Empirical analysis

We begin by demonstrating that eTRS improves seller outcomes, holding seller and listing attributes constant, and then examine three predictions that relate the value of certification to seller reputation and market structure: (1) eTRS has a greater effect on sales probability in product categories where eTRS is rare; (2) eTRS is more valuable in more competitive (low HHI) categories; and (3) the positive effect of eTRS on sales probability is amplified for sellers without long transaction histories. We focus throughout on the matched data where title, subtitle, and seller are identical in order to reduce concerns of unobserved differences across sellers or products. In most cases we additionally limit the sample to observations where listing prices are identical as well.

The basic econometric specification for the matched analysis is:

$$Sale_i = \mu_m + X_i\beta + \gamma eTRS_i + \delta Market_i \times eTRS_i + \theta Seller_i \times eTRS_i + \varepsilon_i. \qquad (1)$$

The dependent variable *Sale* is an indicator for whether a listing *i* ends with a sale. In some specifications we replace *Sale* with *Quantity*, measured as the log of one plus the count of items sold in a listing. There is a fixed effect μ for each group (*m*) of matched items; the vector *X* captures additional observable variation in listing characteristics within the group of matched items, such as impressions, number of photos, and listing duration.[13] We note that both product and seller fixed effects are absorbed by μ. A seller's eTRS status is captured by the variable *eTRS*, with the parameter γ as the marginal effect of the badge on *Sale*. When we turn to examine the heterogeneous effects of certification we also include the interactions between *eTRS* and vectors of market and seller characteristics. The error term ε accounts for additional variation in outcomes across listings. In estimating the parameters in (1), we cluster standard errors at the seller level.

We estimate the parameters in (1) using standard linear regression methods. While this approach does not account for the discrete nature of the dependent variable *Sale*, we are able to include a large number of match-level fixed effects (μ) which would be computationally demanding in nonlinear models. Further, this approach sidesteps the problems associated with

[13] We also estimate our baseline model while restricting the data to STP listings that match on a broader set of attributes, including shipping fees, photo count, listing duration, and quantity of units available. This procedure eliminates only 11% of the STP sample, and our estimates are quantitatively the same as those we report below.

interpreting interaction terms in these nonlinear models. Where possible below, we focus on STP matches to eliminate concerns about estimating γ when sellers might re-price following a transition in certified status. Despite this, in unreported analysis we find that sellers generally do not change matched items' prices after gaining or losing the eTRS badge.

A. Base effects of the eTRS badge

In Table 2, we report the results from our initial estimation of (1), restricting the interaction coefficients δ and θ to equal zero. We include a full set of controls on a listing's timing, duration, shipping fees, and number of photos, but exclude these parameters from Table 2 for brevity of presentation. See Table A1 in the Appendix for the full set of parameter estimates.

Specifications 1-5 in Table 2 employ *Sale* as the dependent variable, while specifications 6-8 use *Quantity*. In specification 1 we estimate the full effect of the eTRS badge on sale probability in Seller-Title-Price (STP) matches, inclusive of the effect of eTRS on search ordering. We find that listings with the badge are 2.2 percentage points more likely to sell, about 8% higher than the base success rate of 27% for unbadged items. In specification 2 we use the log of one plus the number of impressions to control for the effect of the eTRS badge on a listing's position in search results, and we interpret the new estimate of γ to be the "informational" effect of the badge on sale probability. While the magnitude of the badge effect falls slightly, we still find a relatively large impact (7%) on sale probability.[14] The estimate of γ is virtually unchanged when we include the log of views in the model (specification 3), although a consumer's decision to view an item could be affected by the quality-relevant informational value of a badge. In specification 4 we analyze ST matches, which can contain variation in the fixed price of the product, and find a slightly larger estimate of γ. In this specification we observe that the sale probability falls significantly with the log of an item's fixed price. The coefficient on the interaction between log price and the eTRS badge (specification 5) is small in magnitude and statistically insignificant, indicating that both badged and unbadged items have similar price

[14] To further ensure that the coefficient in this specification can be attributed to the informational content of eTRS, we have also tried specifications that control more flexibly for impressions. When we replace log(1 + impressions) with a set of 9 dummy variables that capture the deciles of percentage differences between a listing's number of impressions and the match's mean impressions, we obtain a nearly identical estimate of γ.

elasticities.[15] The results in specifications 6-8, with the log of one plus quantity sold as the dependent variable, are qualitatively similar to those on the sale probability. In specification 6, which controls for the number of impressions, we find that *Quantity* increases by 4% with the addition of the eTRS badge.[16] We report a summary of the badge's effects on impressions and views in Appendix Table A2 – as expected, eTRS has a positive effect on both outcomes. Interestingly, once impressions are accounted for, eTRS has no incremental impact on listing views.

Our estimates of the badge effect and the slope of demand allow us to calculate the trade-off eBay consumers make between quality certification and price. Given the parameter estimates in Table 2 and each listing's characteristics, we can easily calculate the predicted sale probability for each unbadged item in the matched sample. It is also possible to compute the value of Δ such that an unbadged item with the original price p_u has the same sale probability when it is offered at the price of $p_u + \Delta$ by an eTRS seller. For the fixed-price listings in the matched sample, the mean value of Δ is £1.70 and the median value is £0.94. As a percentage of price, the additional willingness-to-pay has a mean of 6.6% and median of 6.7%. When we compute the same price increments using the estimates from specification 8 to equate the expected quantity sold in a listing, we obtain a mean Δ = £1.93 and a median of £0.90.

B. Market characteristics and the value of eTRS certification

Our main contribution is in using our matched data to analyze how product market structure affects the value of eTRS certification. We first examine whether certification's value is affected by product category concentration. To do so, we divide listings into quartiles based on two measures of category-level concentration, averaged within each match: HHI of listings and HHI of quantity sold. We focus exclusively on the sample of STP matches, and all specifications include a full set of listing-level control variables, including the log of one plus impressions.

In the first two columns of Table 3, we present results based on a version of Equation (1) that includes interactions of eTRS status with the four HHI quartile dummies. Whether

[15] We have investigated limiting the sample to ST matches with price variation strictly between the earliest and latest listings (to avoid price reductions that follow from unobserved time trends in demand), and we find similar results. Our estimates of the monetary value of eTRS certification are typically larger than those described here.

[16] We calculate this increase using the point estimate (0.0170) of the badge's effect on log(1+quantity), and the average value of quantity (0.66) among unbadged listings in the ST sample.

competitiveness is measured by listing or quantity HHI, we find that eTRS has a greater effect in less concentrated categories. We estimate an increase in sale probability of 0.024 percentage points for items in the lowest listing HHI quartile, and 0.010 percentage points in the top quartile ($p < 0.01$ for the difference); for quantity-based HHI measures, we estimate coefficients of 0.022 and 0.015 for the lowest and highest quartile interactions, respectively, though the difference between the two is not significant ($p = 0.21$). In specifications 3 and 4, we add controls for a seller's share of all listings or quantity in a category to account for the possibility that the HHI results might actually reflect the impact of the seller's own market share; this has little effect on the coefficient on the HHI-Badge interaction terms.

Thus, our results indicate that quality certification is most important when it helps a firm distinguish itself in a relatively fragmented marketplace. This is consistent with the intuition – captured in a circular city model of product differentiation with heterogeneous seller reliability – that quality certification is more important in the face of intense product market competition.

Our second set of analyses relates the value of certification to the category-level prevalence of eTRS. We present results in Table 4 based on Equation (1), including interactions between eTRS and category-level quartiles for the fraction of listings in a category that possess the eTRS badge. We find that the effect of eTRS is decreasing in eTRS badge prevalence. In specification 1, categories with the lowest-quartile eTRS shares have a badge effect that is nearly three times that of top-quartile categories ($p < .01$ for the difference). The differences are largely unchanged once we normalize the results by the baseline success probabilities within quartiles. Sale probabilities in the lowest quartile increase by 11% with eTRS certification, while those in the highest quartile rise by 4%. We obtain similar results in specifications 2 and 3, when we add controls for a seller's own market share and interaction dummies for the top three HHI quartiles. (Note that this also confirms that our results on concentration are robust to the inclusion of eTRS prevalence.) These findings support the intuition of our learning model, where expected quality is lower in categories where certification is scarce and hence certification causes a higher degree of updating by consumers about a seller's quality in these categories.

The increased sales associated with a given seller may come at the expense of sales by competitors. We examine this "business stealing" effect of certification using a variant on Equation (1) that examines sales probability within a given STP match as category-level eTRS prevalence varies, *holding seller eTRS status constant*. In these analyses, we are identifying the impact of changes in eTRS prevalence based on category-level changes in the prevalence of eTRS across a set of STP matches. For example, a seller may post one listing that closes on the 15th of the month (before eTRS update) and a second identical one closing a week later on the 22nd. As a result of eTRS updates on the 20th, eTRS prevalence may have changed within the listing's category, allowing us to identify the effects of eTRS prevalence using within-match estimates. Thus, our estimating equation is:

$$Sale_i = \mu_m + X_i\beta + \varphi eTRS\_Share_i + \varepsilon_i. \quad (2)$$

where $eTRS_i$ is held constant within m. We estimate (2) with an expanded dataset, which includes matched listings from the 10% platform-wide sample plus those of eTRS sellers whose badge status does not change. In preparing this data we retain the same filters for included listings as we describe in Section 4.B for our main matched sample (i.e., fixed price listings only, price between £4.95 and £500, etc.).

We present our estimation results in Table 5. In specification 1 we report the estimate of equation (2)'s parameter φ within the set of STP matches where *eTRS* = 0. The coefficient is negative and significant at the 1% level, indicating that a 10 percentage point increase in category-level *eTRS* prevalence reduces the probability of sale for non-certified sellers by 0.4 percentage points. (This change in eTRS share is approximately equal to the within-category standard deviation of monthly eTRS shares, 0.087.) Specification 2 presents analogous results for STP matches where *eTRS* = 1. We obtain a slightly larger coefficient, indicating an even greater business stealing effect among certified sellers. The relative sizes of φ across un-badged and badged sellers may be due to a crowding of the quality ladder at the top end when the eTRS share increases.

C. Seller reputation and the value of eTRS certification

In our final set of empirical tests, we examine whether eTRS and customer feedback are substitutes, as one would expect if buyer feedback offered an alternative mechanism for sellers to demonstrate reliability.

In specifications 1 and 2 of Table 6, we examine how seller feedback (averaged over all listings within a match) affects the value of the eTRS badge. We find that the effect of the eTRS badge on sales is amplified for low feedback sellers, suggesting that as feedback increases eTRS certification conveys less (new) quality information to consumers. More precisely, the effect of the eTRS badge on sale probability is roughly twice as large for sellers in the lowest feedback quartile of experience relative to sellers in the highest quartile (0.028 versus 0.013 percentage points). The difference between these parameters is statistically significant at the 1% level. Differences in the baseline sale probabilities across feedback quartiles, however, compress the relative badge effect somewhat. Sale probabilities are 8% higher for sellers in the lowest quartile and 5% greater in the highest quartile.[17]

The overall feedback score contains information on the seller's full history on eBay, which averages 5 years in the matched sample. It is possible that recent activity may be more relevant to consumers, so in specifications 3-5 we measure feedback based on a seller's number of transactions and total revenue in the quarter preceding the listing. We find similar results to those generated using lifetime feedback. One implication of this finding is that eBay's quality certification may help to promote competition in markets because it allows smaller or newer sellers to receive the same quality signal as other sellers, narrowing the information asymmetry gap between them.

D. Impact of eTRS program on Sellers

The analysis above allows us to calculate the value created for sellers by the eTRS badge within the matched sample. Using estimates from specification 6 in Table 2, we calculate total incremental revenue for listings in the STP matched sample due to the eTRS badge to be £5.6 million. To estimate the full impact of the eTRS badge on matched listings inclusive of changes in listing prominence, we re-estimate this equation removing controls for impressions. This estimation yields a coefficient on *eTRS badge* of 0.0224 (standard error 0.0015), corresponding to an increase in total revenue of £7.4 million across all badged listings in the STP matched sample.[18]

[17] In unreported analyses, we have also separated sellers into feedback deciles and find that the badge has a positive and significant effect across the entire feedback distribution. This suggests that consumers are aware that a seller's feedback score is correlated with but never perfectly informative about quality.

[18] Our estimates of 0.0170 and 0.0224 correspond to increases in quantity sold per listing of 0.0285 and 0.0376, respectively. The STP matched sample includes 7.4 M eTRS listings, and the average sale price in the STP matched sample is £26.29.

Extrapolating this estimate to include all eTRS listings, we calculate that the eTRS badge produced £26.8 million in incremental revenue for eTRS sellers.[19] These estimates do not include revenue increases from items sold via true auctions. We view these estimates as reflecting the increase in producer surplus captured by eTRS sellers, akin to the impact of "the treatment on the treated," and note that they are inclusive of supply responses, e.g., decisions by sellers to list more items following the receipt of the eTRS badge.[20] These estimates represent a calculation of gross, rather than net, increase in producer surplus resulting from the eTRS program. The estimates in Table 5 suggest that the eTRS badge promotes a significant shift in sales from non-badge holders to badge-holders.

6. Conclusion

As Arrow (1972) famously noted, "virtually every commercial transaction has within it an element of trust." Private-party certification is one mechanism that enables transaction partners to overcome this trust problem. In theory, certification improves market performance by providing information to buyers that enables them to assess seller quality and attach differences in willingness-to-pay to sellers of various quality levels.

We provide a detailed investigation of a quality certification program on eBay's UK website. This certification program identified "top-rated sellers" who were able to meet a strict set of performance criteria. We use a uniquely rich dataset, with a large number of eBay sellers who offer the same products for sale while transitioning in and out of the certified group, to identify the benefits of receiving quality certification. Our data are also valuable in that they span a very large number of product categories which differ in their levels of competition, further allowing us to examine how the effects of quality certification are affected by market structure.

We find that gaining certification raises the odds of selling a given item by 7%. Holding sale probability constant, the value of certification is equivalent to an increase in £0.94 per item or roughly 6.7% at the median values in the data. Moreover, we find that the incremental value of certification to a seller depends on both market and seller characteristics. Sellers with more

[19] In the 12 months following the introduction of the program, a total of 25.3 million fixed-price items were listed with eTRS status, and the average sale price for listings by sellers who received the eTRS badge at some time during this period was £27.92.

[20] We investigate seller responses to receiving the eTRS badge in a related working paper (Elfenbein, Fisman, McManus 2013).

extensive transaction histories – information that is available to buyers – benefit less from certification than sellers whose quality is relatively less easy to judge. Thus, certification may facilitate entry and/or the expansion of small, high-quality sellers. Additionally our analysis suggests that gaining certification has greater value for sellers in markets that are more fragmented. The benefits of certification also depend on the degree to which competitors possess certification as well. The incremental value of certification to a seller is highest when few rivals have it and is lowest when most rivals possess it. These patterns have implications for market design and firm strategy, and are clearly deserving of future empirical and theoretical attention.

Moreover, our results raise some interesting questions about the impact of certification programs on the evolution of markets. The differential benefit of certification for new versus established players suggests that certification may enable high-quality entrants to grow faster, making concentrated markets more competitive. On the other hand, new entrants of low quality, i.e., sellers that will not attain certification, are at a greater disadvantage in the presence of many other certified sellers, potentially leading them to exit rapidly or deterring their entry altogether. Our results also suggest that these dynamics will be affected by the design of the certification program, specifically whether the quality threshold is set in such a way that enables few versus many market participants to obtain it. We view the dynamic relationship between firm reputation and size, market concentration, and certification design to be a fruitful area for future research.

Our findings have implications for the impact of quality certification within and across many markets. We would predict, for example, that Consumer Reports recommendations or a Good Housekeeping Seal of Approval have different effects on sales of irons versus espresso makers due to differences in market attributes. Moreover, our results suggest that the value of accreditations for high-stakes decisions like hospitals of childcare may vary with local market structure conditions, which could expose some shortcomings in one-size-fits-all public policy recommendations. Our full set of findings is applicable in an array of online markets too, where customer feedback is commonplace, as are expert assessments. The technology review site CNET, for example, offers links to all products in a given category (e.g., HDTVs or desktop computers), while also highlighting those that its reviewers have highlighted as “Best in category.” As with eBay, we expect the value of CNET’s certification would vary by the extent and quality of reader feedback, and also the market structure of a given category.

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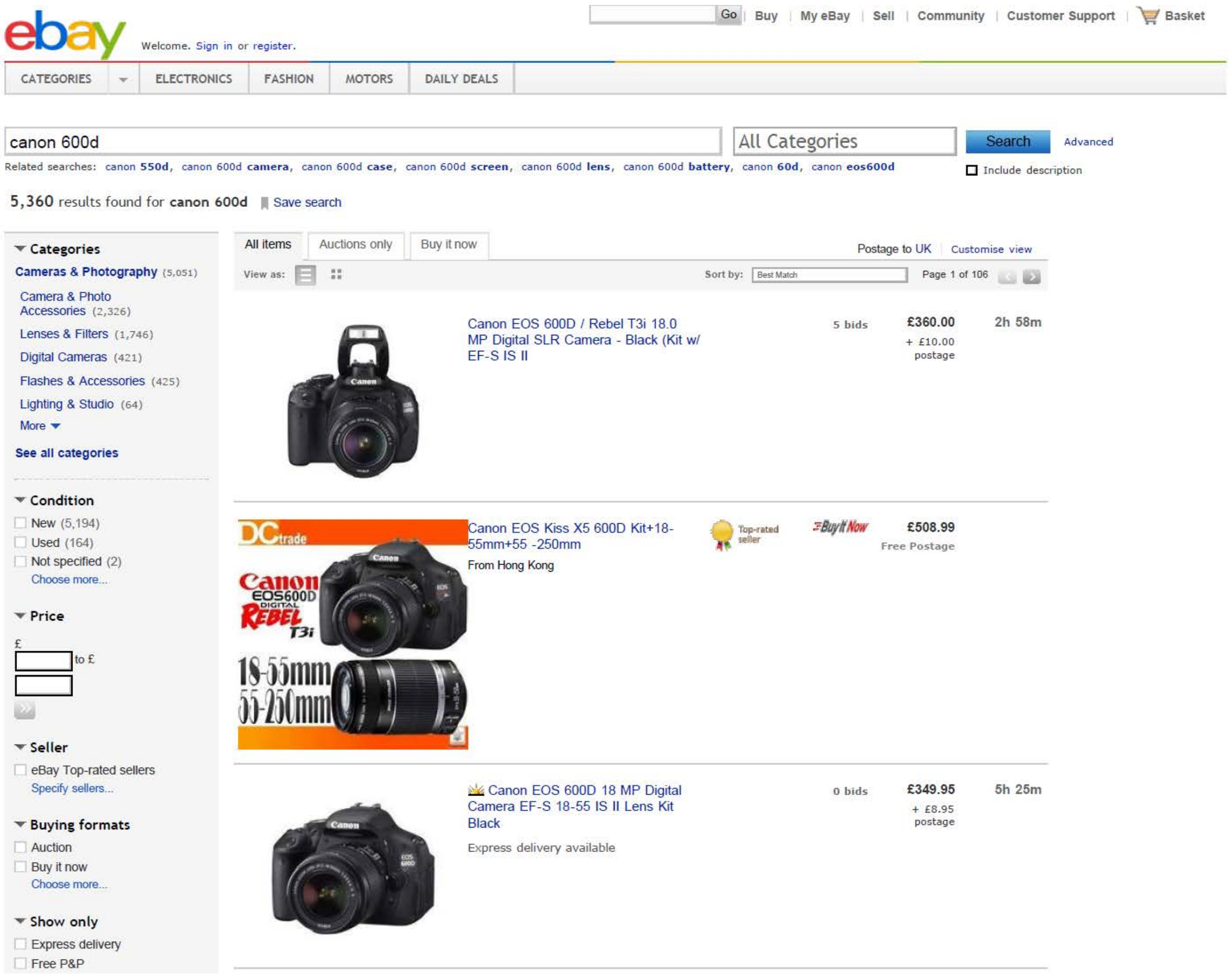
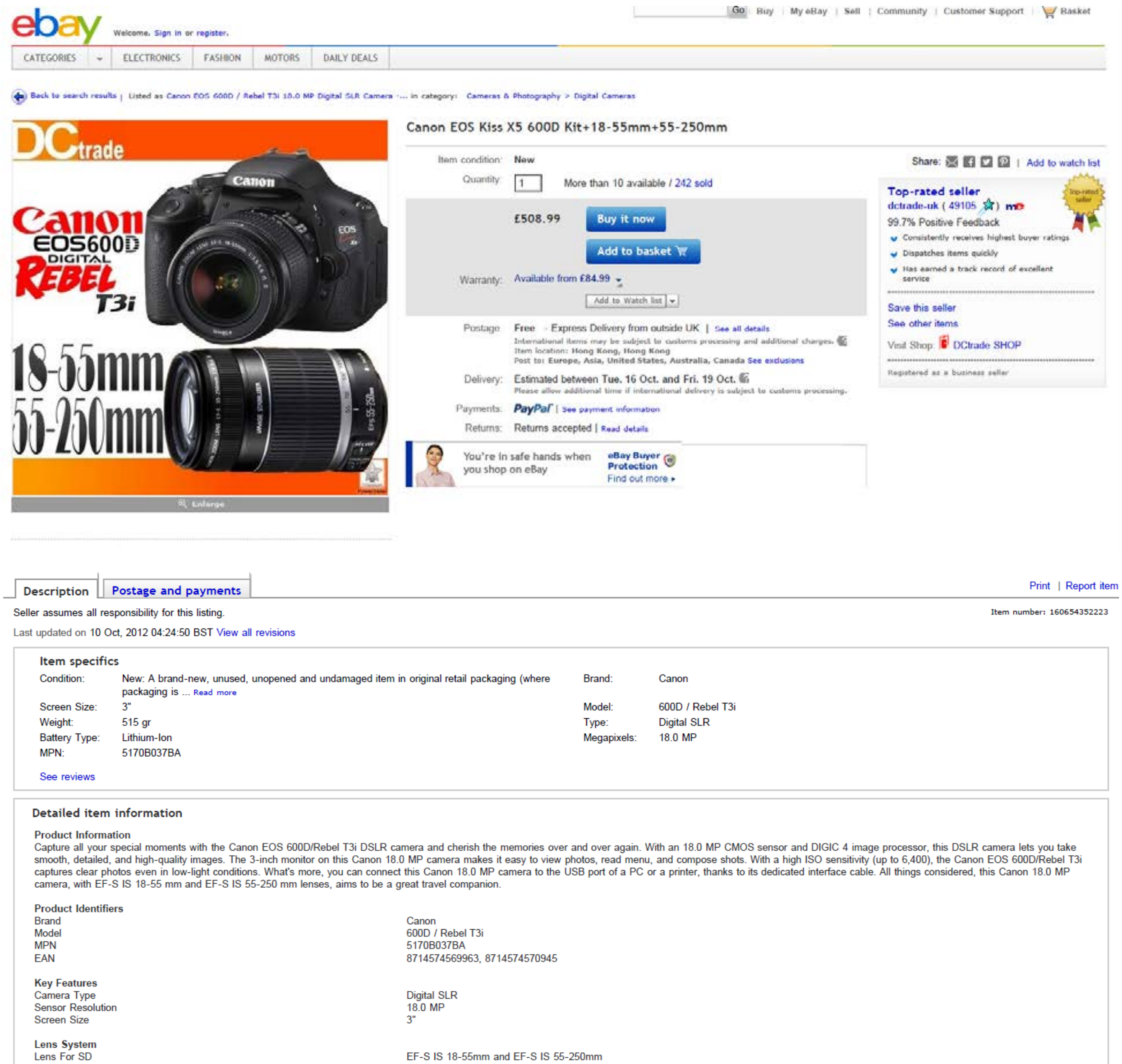
Figure 1. The eTRS badge in search results



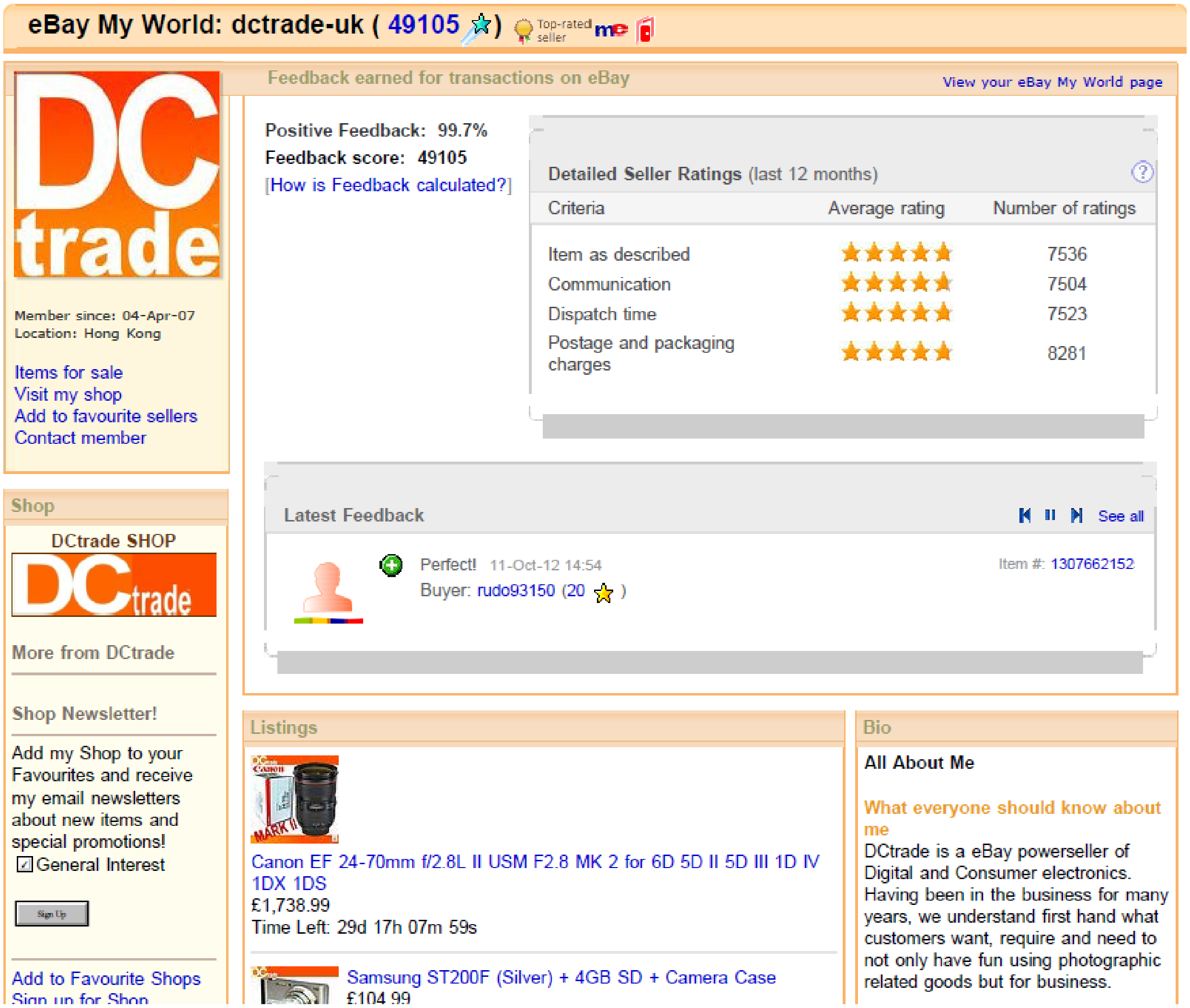
Note: The eTRS badge is found on the second listing in the search results.

Figure 2. The eTRS badge on product listing pages



Note: The eTRS badge is found in the top right corner of the product listing page.

Figure 3. The eTRS badge on seller information pages



Note: The eTRS badge is found next to the feedback score on the top line of the seller information page.

Table 1: Summary statistics for matched sample

	Mean	Median	Std. Dev.	Min	Max
Listings (N = 16,602,455)					
eTRS Badge (Y = 1)	0.52	1	0.50	0	1
Success (Y = 1)	0.27	0	0.45	0	1
Quantity available	23.98	4	90.64	1	1000
Quantity sold	0.68	0	3.44	0	1000
Offered price	28.98	13.99	48.13	0	3499
Price | Sold (N = 4,558,305)	26.29	12.99	43.00	0.99	1117.93
# Impressions	4508.74	1500	9981.86	0	1701247
# Views	41.57	10	132.75	0	26029
Shipping fee	2.57	1.5	5.42	0	6000
# Photos	1.16	1	0.89	0	12
Scheduled length	17.77	10	11.73	1	30
Actual length	15.36	10	11.48	0	47
Category HHI by listings	572.43	265.79	945.50	1.74	10000
Category HHI by quantity	841.41	381.87	1298.02	0	10000
eTRS share in category	0.24	0.21	0.15	0	1
Sellers (N = 24,115)					
# Listings	1317.43	123	10552.16	1	635513
Type-T matches	94.19	12	1410.14	1	176037
Type-P matches	165.31	19	3657.77	1	418240
Feedback score	4282.94	1573.71	11279.34	4.62	737199
Transactions in last 3 mo.	540.74	200.53	1530.07	0	87332
Revenue in last 3 mo.	9820.38	3450.42	45205.14	0	4847815
Category listing share	0.03	0.01	0.07	1.31E-06	0.98
Category sold share	0.04	0.02	0.08	0	0.98

Notes: The "listings" portion of this table contains summary statistics on ST matches in which there is variation in quantity sold. The "seller" portion includes data from all sellers with matches that contribute to the "listings" portion; some of these sellers' listings do not vary in quantity sold.

Table 2: Base results from match analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	Sale	Sale	Sale	Sale	Sale	log(1+Q sold)	log(1+Q sold)	log(1+Q sold)
eTRS badge	0.0219***	0.0182***	0.0193***	0.0202***	0.0262***	0.0170***	0.0189***	0.0313***
	(0.00167)	(0.00164)	(0.00141)	(0.00166)	(0.00508)	(0.00156)	(0.00167)	(0.00515)
log(Price)				-0.313***	-0.312***			-0.295***
				(0.0198)	(0.0198)			(0.0193)
log(Price) X Badge					-0.00215			-0.00456***
					(0.00148)			(0.00157)
log(Impressions)		0.0403***	-0.0255***	0.0372***	0.0372***	0.0584***	-0.0126***	0.0569***
		(0.00275)	(0.00397)	(0.00279)	(0.00279)	(0.00239)	(0.00311)	(0.00247)
log(Views)			0.114***				0.123***	
			(0.00331)				(0.00369)	
Match type	STP	STP	STP	ST	ST	STP	STP	ST
Observations	14,359,591	14,359,591	14,359,591	16,602,455	16,602,455	14,359,591	14,359,591	16,602,455
R-squared	0.008	0.016	0.034	0.025	0.025	0.046	0.067	0.054
Number of matches	1,630,123	1,630,123	1,630,123	1,689,555	1,689,555	1,630,123	1,630,123	1,689,555

Notes: Robust standard errors, clustered by seller, are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. In addition to the listed explanatory variables, the specifications also include controls for listing characteristics such as the number of photos, shipping fee, whether the listing occurred in the first month of the eTRS program, the listing's duration, its ending day of week, and a quartic time trend. See Appendix Table A1 for the full set of controls and their coefficient estimates for specifications 2 and 6.

Table 3: Matched analysis with interactions between eTRS badge and market concentration

	(1)	(2)	(3)	(4)
Dependent variable	Sale	Sale	Sale	Sale
1st quartile listing HHI X Badge	0.0241***		0.0240***	
	(0.00244)		(0.00244)	
2nd quartile listing HHI X Badge	0.0198***		0.0198***	
	(0.00261)		(0.00258)	
3rd quartile listing HHI X Badge	0.0211***		0.0212***	
	(0.00169)		(0.00170)	
4th quartile listing HHI X Badge	0.0101***		0.0103***	
	(0.00324)		(0.00322)	
1st quartile quantity HHI X Badge		0.0221***		0.0217***
		(0.00541)		(0.00533)
2nd quartile quantity HHI X Badge		0.0209***		0.0200***
		(0.00265)		(0.00265)
3rd quartile quantity HHI X Badge		0.0170***		0.0154***
		(0.00201)		(0.00199)
4th quartile quantity HHI X Badge		0.0148***		0.0125***
		(0.00222)		(0.00225)
Seller listing share in cat.			-0.0673***	
			(0.0219)	
Seller listing share in cat. X Badge			0.0532**	
			(0.0225)	
Seller quantity share in cat.				0.320***
				(0.0206)
Seller quantity share in cat. X Badge				-0.0905***
				(0.0180)
Observations	14,359,591	14,359,591	14,359,591	14,345,740
R-squared	0.016	0.016	0.016	0.019
Number of STP matches	1,630,123	1,630,123	1,630,123	1,630,123

Notes: Robust standard errors, clustered by seller, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. See Table 2 notes for additional information on control variables.

Table 4: Matched analysis with interactions between eTRS badge and category eTRS prevalence

	(1)	(2)	(3)
Dependent variable	Sale	Sale	Sale
1st quartile eTRS cat. share X Badge	0.0298***	0.0291***	0.0329***
	(0.00232)	(0.00233)	(0.00301)
2nd quartile eTRS cat. share X Badge	0.0220***	0.0216***	0.0252***
	(0.00198)	(0.00197)	(0.00256)
3rd quartile eTRS cat. share X Badge	0.0189***	0.0189***	0.0230***
	(0.00198)	(0.00194)	(0.00250)
4th quartile eTRS cat. share X Badge	0.0106***	0.0112***	0.0160***
	(0.00200)	(0.00204)	(0.00284)
Seller listing share in cat.		-0.0624***	-0.0625***
		(0.0223)	(0.0222)
Seller listing share in cat. X Badge		0.0495**	0.0527**
		(0.0227)	(0.0228)
2nd quartile listing HHI X Badge			-0.00327
			(0.00313)
3rd quartile listing HHI X Badge			-0.00102
			(0.00282)
4th quartile listing HHI X Badge			-0.0106***
			(0.00398)
Observations	14,359,591	14,359,591	14,359,591
R-squared	0.016	0.016	0.016
Number of STP matches	1,630,123	1,630,123	1,630,123

Notes: Robust standard errors, clustered by seller, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. See Table 2 notes for additional information on control variables.

Table 5: Effects of category eTRS share on sale probability, STP matches

	(1)	(2)
Dependent variable	Sale	Sale
Fixed seller eTRS status	*Badge* = 0	*Badge* = 1
Category eTRS share	-0.0420***	-0.0786***
	(0.00825)	(0.0117)
Observations	7,089,940	9,068,119
R-squared	0.008	0.008
Number of STP matches	992,163	1,171,404

Notes: Robust standard errors, clustered by seller, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. See Table 2 notes for additional information on control variables.

Table 6: Matched analysis with interactions between eTRS badge and seller characteristics

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Sale	Sale	Sale	Sale	Sale
eTRS badge	0.0482***		0.0419***		0.0467***
	(0.00870)		(0.00799)		(0.0119)
log(Feedback) X Badge	-0.00338***				
	(0.00106)				
Fdbk 1st Quartile X Badge		0.0275***			
		(0.00239)			
Fdbk 2nd Quartile X Badge		0.0198***			
		(0.00249)			
Fdbk 3rd Quartile X Badge		0.0166***			
		(0.00234)			
Fdbk 4th Quartile X Badge		0.0133***			
		(0.00388)			
log(Transactions in 3 mo.) X Badge			-0.00346***		
			(0.00127)		
Trans 1st Quartile X Badge				0.0280***	
				(0.00225)	
Trans 2nd Quartile X Badge				0.0216***	
				(0.00197)	
Trans 3rd Quartile X Badge				0.0122***	
				(0.00285)	
Trans 4th Quartile X Badge				0.0166***	
				(0.00401)	
log(Revenue in 3 mo.) X Badge					-0.00296**
					(0.00129)
Observations	14,358,597	14,359,591	14,350,710	14,359,591	14,350,723
R-squared	0.016	0.016	0.016	0.016	0.016
Number of STP matches	1,629,799	1,630,123	1,626,990	1,630,123	1,626,995

Notes: Robust standard errors, clustered by seller, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. See Table 2 notes for additional information on control variables.

Appendix Table A1: Full set of parameter estimates

Specification	(1)	(2)		(1)	(2)
Dependent variable	Sale	log(1+Q)		Sale	log(1+Q)
eTRS Badge	0.0182***	0.0170***	Results continued from left		
	(0.00164)	(0.00156)			
log(impressions)	0.0403***	0.0584***	Sched. Length = 3 (Y = 1)	0.390***	0.994***
	(0.00275)	(0.00239)		(0.0236)	(0.302)
First month of eTRS	0.00681	0.0103	Sched. Length = 5 (Y = 1)	0.397***	0.994***
	(0.00550)	(0.00679)		(0.0218)	(0.302)
First month of eTRS X Badge	0.00380	0.00226	Sched. Length = 7 (Y = 1)	0.410***	0.999***
	(0.00589)	(0.00681)		(0.0211)	(0.302)
log(Shipping fee)	-0.0147***	-0.0144***	Sched. Length = 10 (Y = 1)	0.442***	1.039***
	(0.00147)	(0.00167)		(0.0210)	(0.302)
Photos = 0 (Y = 1)	-0.0973**	-0.0902**	Sched. Length = 30 (Y = 1)	0.616***	1.232***
	(0.0387)	(0.0359)		(0.0230)	(0.302)
Photos = 2 (Y = 1)	-0.00374	0.00225	Time	-0.000284*	-0.000880***
	(0.00688)	(0.00844)		(0.000156)	(0.000172)
Photos = 3 (Y = 1)	-0.00171	0.00819	Time^2	0.000298**	0.000670***
	(0.00788)	(0.0101)		(0.000133)	(0.000152)
Photos = 4 (Y = 1)	0.00647	0.0139	Time^3	-0.00167***	-0.00277***
	(0.00888)	(0.0113)		(0.000451)	(0.000517)
Photos = 5+ (Y = 1)	0.0116	0.0222	Time^4	0.00251***	0.00360***
	(0.0110)	(0.0150)		(0.000513)	(0.000589)
End on Monday (Y = 1)	0.00465***	0.00377***	Qty. avail. in [2, 4] (Y = 1)	0.0483***	0.181***
	(0.00119)	(0.00114)		(0.00649)	(0.00938)
End on Tuesday (Y = 1)	0.00649***	0.00539***	Qty. avail. in [5, 10] (Y = 1)	0.0761***	0.340***
	(0.00126)	(0.00121)		(0.00808)	(0.0142)
End on Wednesday (Y = 1)	-0.000165	0.000714	Qty. avail. in [11, 20] (Y = 1)	0.0938***	0.503***
	(0.00103)	(0.000969)		(0.00780)	(0.0195)
End on Thursday (Y = 1)	-0.00397***	-0.00272***	Qty. avail. in [21, 50] (Y = 1)	0.0876***	0.576***
	(0.00110)	(0.00104)		(0.00899)	(0.0257)
End on Friday (Y = 1)	-0.00842***	-0.00712***	Qty. avail. in [51, 100] (Y = 1)	0.0722***	0.558***
	(0.00102)	(0.000941)		(0.0123)	(0.0329)
End on Saturday (Y = 1)	-0.00869***	-0.00692***	Qty. avail. 101+ (Y = 1)	0.0600***	0.579***
	(0.00103)	(0.000941)		(0.0145)	(0.0388)
			Constant	-0.547***	-1.449***
				(0.0239)	(0.302)
Observations	14,359,591	14,359,591			
R-squared	0.016	0.046			
Number of STP matches	1,630,123	1,630,123			

Notes: Robust standard errors, clustered by seller, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A2: Effects of eTRS Badge on Impressions and Views

	(1)	(2)	(3)
Dependent variable	Log(Impressions)	Log(Views)	Log(Views)
eTRS badge	0.0909***	0.0432***	-0.00873
	(0.0155)	(0.0132)	(0.00668)
Log(impressions)			0.571***
			(0.0111)
log(shipping)	0.849	1.878***	1.393***
	(0.700)	(0.411)	(0.0437)
3-day listing	1.006	1.880***	1.305***
	(0.699)	(0.410)	(0.0307)
5-day listing	1.152	1.990***	1.333***
	(0.700)	(0.410)	(0.0319)
7-day listing	1.278*	2.045***	1.315***
	(0.697)	(0.410)	(0.0261)
10-day listing	1.642**	2.305***	1.368***
	(0.698)	(0.410)	(0.0398)
30-day listing	0.849	1.878***	1.393***
	(0.700)	(0.411)	(0.0437)
Observations	16,602,455	16,602,454	16,602,454
R-squared	0.161	0.175	0.628
Number of matches	2,807,935	2,807,935	2,807,935

Notes: Robust standard errors, clustered by seller, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. In addition to the listed explanatory variables, the specifications include the additional control variables discussed Table 3’s notes and provided in Appendix Table A1.

Appendix

1. Product market competition and the value of certification

We model product market competition as a variant on Salop's (1979) circular city. Consumers are distributed with unitary mass around a circle of unit circumference. N sellers, each with marginal cost of c, are spaced evenly around a circle of unit length.[21] For consumers, we assume linear travel costs t and utility from the good of u. Sellers differ in their ability to successfully complete transactions. We assume that α_i represents the probability that the i^{th} seller completes transactions successfully. We model reliability as being a binary attribute, with low-type (high-type) sellers having reliability of α_L (α_H). In the absence of additional information on individual seller quality, consumers expect utility from the good of $E(\alpha)u$, where the expectation of α simply comes from the fraction of high types in the seller population, which we assume to be ϕ. Without additional information on a seller, $E(\alpha) = (1 - \phi)\alpha_L + \phi\alpha_H$.

We assume travel costs are sufficiently high that all consumers buy from one of the two closest firms. A consumer located a distance x from seller i is indifferent between buying from i and his neighbor $i + 1$ if:

$$E(\alpha_i)u - p_i - tx = E(\alpha_{i+1})u - p_{i+1} - t(1/N - x)$$

For the simple symmetric equilibrium case where all firms have the same expected reliability, $E(\alpha)$, seller i's demand is given by $q_i = (p - p_i + t/N)/t$, where p is the equilibrium price. Maximizing profits with respect to p_i generates $p = c + t/N$, with market shares of $1/N$.

Within the context of this symmetric equilibrium, consider the effects of seller i obtaining certification from eBay, assuring consumers that $\alpha_i = \alpha_H$. Holding the prices of other sellers constant, i's demand becomes:

$$q_i = [p - p_{\mathrm{i}} + (\alpha_{\mathrm{H}} - E(\alpha)) + t/N]/t$$

[21] Since we will take the number of firms as exogenous, we ignore fixed (entry) costs.

If seller i keeps his price constant – effectively the situation that we capture with our seller-title-price matched dataset – then seller i's demand increases to $1/N + [\alpha_H - E(\alpha)]/t$. The percentage increase in demand from certification is thus given by:

$$[(1/N + [\alpha_H - E(\alpha)]/t) - 1/N]/(1/N) = N[\alpha_H - E(\alpha)]/t$$

That is, since there is a fixed increase in demand from certification, in proportional terms the impact is increasing in product market competition N.

2. Seller feedback, category quality, and the value of certification

We again assume there are two types of sellers: high-types that complete transactions successfully with probability α_H, and low-types that are successful with probability α_L, and that the overall frequency of high-type sellers is ϕ, so the share of low-type sellers is $(1 - \phi)$. Before the seller posts any listings, eBay observes the seller's true quality with probability λ. If eBay observes that the seller is type H, eBay awards it an eTRS badge, so that $B = 1$. In all other cases, $B = 0$. After each transaction, consumers make a public feedback announcement f. Consumers report $f = 1$ if the transaction was good, and $f = 0$ if the transaction was bad.

We examine consumer inferences about seller quality for the seller's first two trades. Before deciding whether to buy a product, potential consumers observe the seller's state, (F,N,B). F is the sum of all prior feedback, N is the number of completed trades, and B is badge status. F, N, and B each take values in $\{0, 1\}$.

We define the badge premium as $\pi(F,N) = E(\alpha|F,N,1) - E(\alpha|F,N,0)$. By assumption $E(\alpha|F,N,1) = \alpha_H$ regardless of F and N. Consumers calculate $EU = E(\alpha|F,N,B)u - p$, where u is gross value from a perfect transaction and p is price.

We next provide some definitions that simplify our exposition. Let w_L and w_H represent non-negative constants, and use them to form the probability weights ρ_L and ρ_H. We construct $\rho_a = w_a/(w_H + w_L)$. Clearly $\rho_H + \rho_L = 1$. Holding w_L fixed, ρ_L is decreasing in w_H, while ρ_H is increasing. For the expected value $E(\alpha) = \rho_H\alpha_H + \rho_L\alpha_L$, it follows from the construction of the ρ and w terms that greater values of w_H for fixed w_L imply greater values of $E(\alpha)$.

Our interest is in modeling how consumers' beliefs about seller type evolve over rounds of trade and differ across product categories, which then allows us to compare certification premia across different seller and category traits.

A. Seller feedback and the value of certification

Before the first round of trade

Before any trade has occurred a seller has $F = N = 0$, and B is equal to 0 or 1. The probabilities of the two possible seller states are:

$$Pr(0,0,1) = \lambda\phi$$
$$Pr(0,0,0) = (1-\lambda)\phi + (1-\phi).$$

The certification rules immediately provide two conditional probabilities: $Pr(\alpha_H|0,0,1) = 1$ and $Pr(\alpha_L|0,0,1) = 0$. Applying Bayes' rule, the additional conditional probabilities are:

$$Pr(\alpha_H|0,0,0) = \frac{(1-\lambda)\phi}{(1-\lambda)\phi+(1-\phi)}$$
$$Pr(\alpha_L|0,0,0) = \frac{(1-\phi)}{(1-\lambda)\phi+(1-\phi)}.$$

A consumers who sees $B = 1$ immediately infers $E(\alpha|0, 0, 1) = \alpha_H$. Alternatively, in state (0, 0, 0) the consumer calculates:

$$E(\alpha|0,0,0) = \frac{\alpha_H(1-\lambda)\phi+\alpha_L(1-\phi)}{(1-\lambda)\phi+(1-\phi)}.$$

Note that this expected value can be written as $E(\alpha|0, 0, 0) = \rho_H\,\alpha_H + \rho_L\alpha_L$ with appropriately defined probabilities ρ_a. The badge premium $\pi(0,0) = \alpha_H - E(\alpha|0,0,0)$ is positive. This is clear from the probabilities $\rho_H < 1$ and $\rho_L > 0$ in $E(\alpha|0,0,0)$.

Before the second round of trade

A seller's first round of trade will yield feedback *f*, so *F* will be 0 or 1. *N* automatically increases to 1. The seller's certification state, *B*, does not change. Possible seller states are (0, 1, 0), (1, 1, 0), (0, 1, 1), and (1, 1, 1). The various states' probabilities are:

$$Pr(0,1,0) = (1-\alpha_H)(1-\lambda)\phi + (1-\alpha_L)(1-\phi)$$
$$Pr(1,1,0) = \alpha_H(1-\lambda)\phi + \alpha_L(1-\phi)$$
$$Pr(0,1,1) = (1-\alpha_H)\lambda\phi$$
$$Pr(1,1,1) = \alpha_H\lambda\phi.$$

These state probabilities yield the following conditional probabilities:

$$Pr(\alpha_H|0,1,0) = \frac{(1-\alpha_H)(1-\lambda)\phi}{(1-\alpha_H)(1-\lambda)\phi+(1-\alpha_L)(1-\phi)}$$
$$Pr(\alpha_L|0,1,0) = \frac{(1-\alpha_L)(1-\phi)}{(1-\alpha_H)(1-\lambda)\phi+(1-\alpha_L)(1-\phi)}$$
$$Pr(\alpha_H|1,1,0) = \frac{\alpha_H(1-\lambda)\phi}{\alpha_H(1-\lambda)\phi+\alpha_L(1-\phi)}$$
$$Pr(\alpha_L|1,1,0) = \frac{\alpha_L(1-\phi)}{\alpha_H(1-\lambda)\phi+\alpha_L(1-\phi)}.$$

Note again that for all states with *B* = 1, $Pr(\alpha_H) = 1$. The relevant expected values are thus:

$$E(\alpha|0,1,0) = \frac{\alpha_H(1-\alpha_H)(1-\lambda)\phi+ \alpha_L(1-\alpha_L)(1-\phi)}{(1-\alpha_H)(1-\lambda)\phi+(1-\alpha_L)(1-\phi)}$$
$$E(\alpha|1,1,0) = \frac{\alpha_H^2(1-\lambda)\phi+ \alpha_L^2(1-\phi)}{(1-\lambda)\alpha_H\phi+\alpha_L(1-\phi)}.$$

We use these expressions to calculate certification premia, and also to compare the premia to those that obtain prior to the first round of trade. Consider the difference between the no-feedback premium, $\pi(0,0) = \alpha_H - E(\alpha\,|0,0\ 0)$, and the premium with one unit of positive feedback, $\pi(1, 1) = \alpha_H - E(\alpha\,|1,1\ 0)$. This difference is:

$$\pi(0,0) - \pi(1,1) = E(\alpha|1,1,0) - E(\alpha|0,0,0)$$

$$= \frac{\alpha_H^2(1-\lambda)\phi + \alpha_L^2(1-\phi)}{(1-\lambda)\alpha_H\phi+\alpha_L(1-\phi)} - \frac{\alpha_H(1-\lambda\phi)+\alpha_L(1-\phi)}{(1-\lambda)\phi+(1-\phi)}.$$

We simplify the difference by replacing $w_H = (1-\lambda)\phi$ and $w_L = (1-\phi)$, and dividing the numerator and denominator of $E(\alpha|1,1,0)$ by α_L:

$$\pi(0,0) - \pi(1,1) = \frac{\alpha_H(\alpha_H/\alpha_L)w_H + \alpha_L w_L}{(\alpha_H/\alpha_L)w_H + w_L} - \frac{\alpha_H w_H + \alpha_L w_L}{w_H + w_L}.$$

Next, we set $(\alpha_H/\alpha_L)w_H = \widetilde{w}_H$, and note that $w_H < \widetilde{w}_H$. Following the properties of ws discussed above, we see that the premium difference is positive, so that the certification premium is greater when no feedback has yet occurred.

While it is possible to also generate comparisons across different *F/N* ratios, the precise properties would depend on the precise specification of how we model feedback, and in any event our results on the case of $F = N$ serve as the clearest representation of the link between more positive feedback and the value of certification.

B. Cross-category comparisons on the value of certification

We now augment the model by assuming that some product categories are riskier than others; we further assume that sellers do all of their trade in a single category. We model category risk through ϕ, and say that category j is riskier than k if $\phi_j < \phi_k$. Holding fixed the eBay investigation parameter λ (as is the case in practice) fewer sellers will receive $B = 1$ in a higher-risk category because there are fewer high-quality sellers.

We constrain $F = N$ and let $\pi_j(F)$ be the certification premium in a category with high-quality share ϕ_j. We compare premia across categories through the difference $\pi_j(F) - \pi_k(F)$ for $\phi_j < \phi_k$. If we extrapolate our expression for $E(\alpha_H|1,1,0)$ expression above to the general case of F, we may write the relevant difference as:

$$\pi_j(F) - \pi_k(F) = \frac{\alpha_H^{F+1}(1-\lambda)\phi_k + \alpha_L^{F+1}(1-\phi_k)}{\alpha_H^F(1-\lambda)\phi_k+\alpha_L^F(1-\phi_k)} - \frac{\alpha_H^{F+1}(1-\lambda)\phi_j+\alpha_L^{F+1}(1-\phi_j)}{\alpha_H^F(1-\lambda)\phi_j+\alpha_L^F(1-\phi_j)}$$

Replacing $w_{Hk} = \alpha_H^F(1-\lambda)\phi_k$ and $w_{Lk} = \alpha_L^F(1-\phi_k)$, and defining analogous values of w_{Hj} and w_{Lj}, we may write the difference as:

$$\pi_j(F) - \pi_k(F) = \frac{\alpha_H w_{Hk} + \alpha_L w_{Lk}}{w_{Hk} + w_{Lk}} - \frac{\alpha_H w_{Hj} + \alpha_L w_{Lj}}{w_{Hj} + w_{Lj}}.$$

Next, multiply the w_{Lk} terms by $\frac{1-\phi_j}{1-\phi_j}$ and the w_{Hk} terms by $\frac{\phi_j}{\phi_j}$. This yields:

$$\pi_j(F) - \pi_k(F) = \frac{\alpha_H w_{Hj}(\frac{\phi_k}{\phi_j}) + \alpha_L w_{Lj}(\frac{1-\phi_k}{1-\phi_j})}{w_{Hj}(\frac{\phi_k}{\phi_j}) + w_{Lj}(\frac{1-\phi_k}{1-\phi_j})} - \frac{\alpha_H w_{Hj} + \alpha_L w_{Lj}}{w_{Hj} + w_{Lj}}.$$

Notice that we have eliminated w_{Hk} and w_{Lk}. We now multiply the top and bottom of the first term by $(\frac{1-\phi_j}{1-\phi_k})$ to get:

$$\pi_j(F) - \pi_k(F) = \frac{\alpha_H \widetilde{w}_{Hj} + \alpha_L w_{Lj}}{\widetilde{w}_{Hj} + w_{Lj}} - \frac{\alpha_H w_{Hj} + \alpha_L w_{Lj}}{w_{Hj} + w_{Lj}}$$

$$\text{with} \qquad \widetilde{w}_{Hj} = w_{Hj}\left(\frac{\phi_k}{\phi_j}\right)\left(\frac{1-\phi_j}{1-\phi_k}\right)$$

The final remaining step is to show that $\widetilde{w}_{Hj} > w_{Hj}$, which follows directly from the assumption that $\phi_j < \phi_k$, since both $\left(\frac{\phi_k}{\phi_j}\right)$ and $\left(\frac{1-\phi_j}{1-\phi_k}\right)$ are greater than one. Thus, certification's value will be greater in markets where certification is rarer due to category risk.