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

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This draft: April 2014

Abstract

Quality certification programs help consumers 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 impact on consumer demand varies 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, Georgia Tech, UCLA, the University of North Carolina – Charlotte, the University of Michigan, and the University of Minnesota for their helpful comments.

1. Introduction

Quality certification as a means of reducing "lemons" problems is a common feature across a range of markets, including consumer retail, firm-to-firm trade, labor markets, and specialty services like medical treatment and auto repair.[1] The ubiquity of "expert" guidance from certifiers like Consumer Reports, city hygiene departments, and various hospital credentialing organizations, to name just a few, 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.

Empirical 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 fundamental questions, such as: How does the number of competing products on nearby store shelves or webpages affect consumer responses to certification? 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 certification's quality threshold affect its impact on consumer choices? And how do alternative reputational signals like crowd-sourced feedback affect the value of certification? Developing a better understanding of the differential impact of certification as a function of seller or industry attributes can help to assess how the introduction of certification mechanisms is likely to affect industry evolution, including firm entry and market power, and to anticipate what types of firms will gain and lose as a result. Evaluating the heterogeneous effects of certification may also aid in the design of certification programs themselves, providing guidance, for example, on the choice of quality threshold requirements and how the program might be influenced by industry attributes like the scope for opportunism.

To begin addressing these questions, we examine the impact of eBay's Top-Rated Seller (eTRS) certification using a dataset comprised of 1.6 million "quasi-experiments"

[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).

run by nearly 23,000 sellers in more than 8,000 distinct product categories in the United Kingdom. These quasi-experiments feature variation in sellers' certification status for otherwise identical products offered for sale. Identical criteria are used to evaluate all sellers for certification, independent of the category where they place their listings. By taking advantage of heterogeneity across product categories and sellers, we examine how consumer responses to certification vary across markets that differ in concentration and in underlying quality uncertainty, and how certification's impact varies with sellers' scale and reputation.

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. Specifically, we are able to isolate and analyze cases where sellers list identical items at the same price with and without certification, enabling us to capture the impact of certification on demand, holding price (and other attributes) constant. Moreover, 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 control for the "advertising" impact of certification, and to separate this from its informational content on seller quality. In most contexts, it is difficult to make this distinction: for example, Consumer Reports puts top-ranked items first, and may not even list lesser-quality products.

A priori, it is unclear how differences in market attributes affect the impact of certification on consumer demand. If transaction risk, conditional on observables, is identical across sellers then certification's premium could be independent of the proportion of certified sellers in the marketplace. Alternatively, if a scarcity of certified sellers is interpreted by consumers as a sign of significant quality concerns in the marketplace, certification's value may be decreasing in the proportion of certified sellers. 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. Our findings offer some guidance in assessing which of these effects dominate empirically.

To provide a conceptual underpinning for the empirical regularities we do 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. Modeling competition as horizontal product differentiation, we also 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 – displayed to consumers via a small eTRS "badge" on all of a seller's listings – is associated with a significant increase in demand even when controlling for the impact of certification on the listing's prominence in search results. Across our sample, certification increases by 7% the probability that a given seller's fixed-price listing ends successfully with a sale. Combined with price sensitivity estimates, our findings imply that 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 £0.89 will generate equal sale probabilities between badged and unbadged items for a given seller. 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 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 at the 25th percentile of eTRS listing frequency, certification's impact is roughly 50% greater than in markets at the 75th percentile. 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. The badge's impact is almost twice as large in eBay markets at the 25th percentile of seller concentration relative to those at the 75th percentile.

We then 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 25th percentile of those in the matched sample have an increase in sale probability from the badge that is 45% greater than the badge effect of sellers at the 75th percentile. Thus, certification's impact is amplified for sellers with relatively few past sales transactions, who have not yet had the opportunity to demonstrate their reliability to prospective buyers via a record of satisfactory transactions.

Finally, we examine whether growth in eTRS certification generates a "business stealing" effect by reducing the sales of competitors. We find that an increase in eTRS prevalence has a negative effect on other sellers in a category, particularly already-certified ones, consistent with more widespread certification promoting greater competition among high-quality sellers. Collectively, our findings highlight that the impact of quality certification on a particular seller – and hence the seller's incentives to acquire and maintain certification – depends on the characteristics of both the seller and the market, and generates a differential competitive impact on uncertified versus certified sellers.

We emphasize that while eBay serves as a particularly convenient context for studying these issues, the questions we address have implications for the role of certification across a wide range of consumer products and certification mechanisms. For example, Consumer Reports recommendations or a Good Housekeeping Seal of Approval may have different effects on sales of irons versus high-end espresso makers due to differences in market attributes. This also implies that quality assessment organizations should take market conditions into account in designing certification mechanisms, and that one-size-fits-all accreditations may not be optimal. Given the ubiquity and importance of services rated by such accreditation bodies – from hospitals to child care to education – understanding how to tailor certification mechanisms to "local" circumstance is an issue of first-order importance.

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. In later work, Jin and Leslie (2009) go on to compare certification's impact on chain versus non-chain establishments in a study of the interaction among certification, reputation, and cross-restaurant information spill-overs, but they are unable to perform the type of cross-market analysis that forms the core of our paper.

In a similar spirit to Jin and Leslie (2003), 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. Some evidence exists, however, suggesting that certification's impact may be attenuated by features of the institutions and market studied. 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, while Ho (2012) describes how grade inflation and grading inconsistency may subvert the goals of restaurant hygiene systems in a variety of US cities.[2] In a study of quality assurance mechanisms introduced on eBay's platform in the United States, Hui et al. (2013) document the reduction in certification's impact when a new buyer protection program was added to the website. To our knowledge, we are the first to examine how differences in market-level attributes affect consumers' responses to certification.

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. 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.

[2] In some cases, firms' pursuit of quality certification can have unintended or perverse effects. Dranove et al. (2003) show that hospitals may decline to treat 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 improve 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 (for example, Moody's) 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).

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 one of the world's largest online marketplaces. In 2012, 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 became by 2012 eBay's second most active marketplace, after the US-based site. According to the web information provider Alexa, ebay.co.uk's global web traffic rank in 2012 was 85, and sixth within the UK; by comparison www.ebay.com, was ranked 23 worldwide and seventh in the US that year.[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.

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

[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

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 generate public track-records about 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.

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, for example, Bolton et al. 2012; Brown and Morgan 2006; Dini and Spagnolo 2009). 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

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figures are 99.7 and 95.4 percent, respectively. See Einav et al (2013b) for a discussion of the decline of auctions on eBay.

[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.

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 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.

[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."

Top-Rated Seller status is assessed monthly. On the 20th day of each month, eBay evaluates seller performance over the three months prior to that date (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

[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.

sort results by time, price, or distance. In our 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 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 impact of certification on consumer demand are not clear *a priori*. 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 (consistent with the quasi-experiments we examine), 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 for consumers: (1) *Certification's impact is decreasing in the fraction of sellers in an industry that are quality-certified*, and (2) *Certification's impact 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 consumers click-through to the listing's full webpage (a "view"). 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 33 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.

[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.

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. (2013a) 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 certification's 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. (One potential concern is that STP-matches might not represent pure quasi-experiments, as sellers can adjust prices in response to receiving eTRS status. Empirically, we find no evidence that sellers respond in this way to certification, as we discuss in Section 5 below.)

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 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

[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.

[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.

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 by sellers for whom we have complete data. Within these listings, we restrict our attention to the 16.3 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).[13]

In Table 1 we summarize the listing-level characteristics of the final set of ST matches. Out of 16.3 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 £26.32 (median £12.99) for successful transactions, which is slightly below the average posted price among the matched listings. The average number of units sold per listing (0.67) is greater than the overall success rate due to successful sales of multiple units from a single listing.

Our sample of 16.3 million fixed-price listings contains data from 22,801 sellers, whose characteristics are summarized at the bottom of Table 1. The median seller has 134 listings across 13 ST matches. The mean and median feedback scores are 4268 and

[13] If we were to retain observations with no variation in the outcome variable, the coefficient on eTRS would be biased toward zero in our linear probability model. The intuition is as follows: a binary-outcome econometric model's latent equation can contain a non-zero eTRS effect while allowing a large negative fixed effect to match an empirical result that all items in a group fail to sell. The linear probability specification makes no distinction between the latent and observed models, however, and when no objects in a group sell the least-squares estimates of all coefficients are pushed toward zero. (The same argument applies to a group of listings in which all items sell.)

1562, respectively, indicating that this group of sellers is well-established on the eBay platform. The median seller has 202 successful transactions per quarter and £3472 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.

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 market structure and seller reputation: (1) eTRS will have a greater effect on sales probability in product categories where eTRS is rare; (2) eTRS will be more valuable in more competitive (low HHI) categories; and (3) the positive effect of eTRS on sales probability will be 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:

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

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. We note that both product and seller fixed effects are absorbed by μ. A seller's eTRS status is captured by the variable *eTRS Badge*, 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 Badge* 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 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. We note that our potential concerns about re-pricing – and hence whether price variation is exogenous in ST matches – are alleviated by additional empirical analysis, reported in Table S1 in the supplementary online appendix, which shows that a change in badge status results in a precisely measured zero average change in posted price. To the extent that sellers change strategies after acquiring eTRS status, it may occur through the number and value of items listed on eBay rather than price-setting.[14]

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 to make the presentation more concise. 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

[14] While we find some evidence that sellers *lower* their shipping fees after receiving certification, this unusual pattern appears to pose no problems for our core intuition or inference.

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.[15] 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 *eTRS Badge* (specification 5) is small in magnitude and statistically insignificant, indicating that both badged and unbadged items have similar price elasticities.[16] In both the tables and associated text that follows we use *Badge* as a shorthand for *eTRS Badge* when referring to interaction terms.

As a final robustness check, in in specifications 6-8 we employ the log of one plus quantity sold as the dependent variable, and obtain results that are qualitatively similar to those on the sale probability. In specification 6, which controls for the number of

[15] 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.

[16] As noted above, we take this price variation to be exogenous, possibly as a result of experimentation by the seller. (See Einav et al. (2013a) for an extensive discussion of seller experimentation on eBay's US platform, and its usefulness in estimating the slope of demand.) The presence of product-specific fixed effects and time trend controls allay many of the usual concerns about price endogeneity. Our finding of zero average price response from receiving the badge, noted above, further validates the use of this variation in our demand-side analysis.

impressions, we find that *Quantity* increases by 4% with the addition of the eTRS badge.[17]

In Appendix Table A2, we provide a number of further robustness checks for our estimates of γ. To account for possible within-match heterogeneity in listing attributes, in specification 1 we repeat our main analyses with a much more stringent match requirement, where within a match all listings are identical in terms of title, subtitle, and price, as well as number of photos, shipping fee, scheduled length, quantity available. Our estimate of eTRS's impact on demand within these 'super-matches' is very similar to that obtained in our main analysis. In the second specification of Table A2, we limit our sample to listings where there had been a change in eTRS status between the current month and either the preceding or next one, and in the third specification we include only listings that conclude in the 20-day period spanning the ten days prior to an eTRS status change and the ten days following it. By focusing on the window immediately around status changes, we are better able to isolate demand-side responses to eTRS from possible post-certification seller responses or time trends. We obtain point estimates that are very similar to those in Table 2, and when we apply the appropriate baseline sale probabilities (based on the sample window) to these coefficients, we find that the eTRS badge shifts the sale probability by 8% in both cases. Finally, we report results using the fraction of time during an item's listing period when the seller held eTRS status (rather than an indicator variable for eTRS status at the end of listing); once again the point estimate indicates a similar impact of eTRS status on demand.

We report a summary of the badge's effects on impressions and views in Appendix Table A3 – as expected, eTRS has a positive effect on both outcomes. Interestingly, once impressions are accounted for, eTRS has no incremental impact on listing views. These regressions, along with the nearly 20% difference in the estimates of γ between columns 1 and 2 in Table 2 above, illustrate the importance of controlling for the prominence effects of certification in assessing its (informational) impact.

[17] We calculate this increase using the point estimate (0.0171) of the badge's effect on log(1+*Quantity*), and the average value of quantity (0.66) among unbadged listings in the ST sample.

Our estimates of the badge effect and the slope of demand also 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, it is straightforward to 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 £1.65 and the median value is £0.89. As a percentage of price, the additional willingness-to-pay has a mean of 6.7% and median of 6.8%. 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 = £1.27 and a median of £0.88.

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: there are 7.4 million eTRS listings in the STP sample, with an average sale price of £26.29, and the coefficient estimate of 0.0171 implies an increase in quantity sold of 0.0285 per listing. Hence the increment to revenue is £5.6 million (£7.4 million if we remove controls for impressions). Extrapolating this estimate to include all eTRS listings, we calculate that the eTRS badge produced £26.8 million in incremental revenue for eTRS sellers.[18]

B. Market characteristics, seller characteristics and the impact of eTRS certification

Our main contribution is in using our matched data to analyze how product market structure and seller characteristics affect the impact of eTRS certification on demand. We examine these effects by estimating (1), with a focus on parameters δ and θ, which represent the interaction between *eTRS Badge* and market characteristics and seller

[18] 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.

characteristics, respectively. In particular, we examine the predictions from section 3, that the impact of certification on demand should decline in market concentration, the proportion of sellers in a product category with certification, and the observable track record of the seller.

Table 3 presents our main results; we follow with a discussion of a number of alternative specifications and robustness checks, with results provided in a series of online appendices. In all regressions, we control for impressions, so we interpret our estimates of the market and seller characteristics' effect on eTRS badge value as representing changes in impact due to information rather than listing visibility.

We begin by examining in specification 1 the impact of industry concentration on the value of certification by including the interaction of *eTRS Badge* and the category-level variable *Listings HHI* in (1). We divide all HHI statistics by 1,000 so that the regression coefficients are easy to read. The coefficient on the badge-HHI interaction is -0.00374, and significant at the 1% level. The attenuating effect of concentration is consistent with the intuition captured by the simple circular city model described in Section 3 above. The estimated coefficient is economically meaningful: it implies that the badge's effect at the 25th percentile of *Listings HHI* (118) is 10% greater than the effect at the 75th percentile HHI value (610). *Listings HHI* has an extremely long right tail, raising the concern that this result may be driven by outliers. We therefore employ the transformed variable, log(*Listings HHI*) (which has a smooth, normal distribution) in specification 2; these results imply a much larger reduction in the badge's impact (47%) between the 25th and 75th percentiles of HHI.

In specification 3, we examine how the value of certification varies with the category-level prevalence of eTRS by including an interaction between *eTRS Badge* and *eTRS Share*, the fraction of listings (in the most narrowly defined category) with eTRS status. The coefficient is -0.0477, significant at the 1% level. Moving from the 25th to 75th percentile of *eTRS Share* (14% to 31%), the estimates imply a reduction in the badge's effect by one-third. This result, too, is consistent with the modeling exercise described in Section 3, where consumers infer that categories with a greater proportion of certified listings have fewer quality problems, thus reducing the difference in performance expected from sellers with and without certification. In specification 4 we include both *Listings HHI* X *Badge* and *eTRS Share* X *Badge* simultaneously. The coefficient on the *eTRS Share* interaction is virtually unchanged, while the *Listings HHI* interaction loses its significance. One concern with this specification is that very highly concentrated categories will, almost by definition, take on extreme values on *eTRS Share*, mechanically increasing variation in this variable due to market structure rather than inherent category risk. This occurs most strongly at the upper tail of the HHI distribution, and replacing *Listings HHI* with its log transformation reduces impact of extreme HHI values. In specification 5, when we use the log(*Listings HHI*) to represent market concentration, we find that both interaction terms retain significant explanatory power.

Next, in specification 6 we examine the prediction that certification and seller track record are substitutes, through the inclusion of log(*Feedback*) X *Badge*. Consistent with the two forms of quality signals serving as substitutes, the coefficient on the interaction terms is negative, taking on a value of -0.00335 (significant at the 1% level). Moving from the 25^{th} to 75^{th} percentile of seller feedback entails a reduction in the badge's impact by 30%. In specification 7, we include all three interactions – log(*Listings HHI*) X *Badge*, *eTRS Share* X *Badge*, and log(*Feedback*) X *Badge* – simultaneously, and find that all three variables continue to have significant explanatory power.

To address the concern that there may be category-level attributes correlated with eTRS share or concentration that also affect eTRS value, in Table 4 we include fixed effects for each of eBay's 33 meta-categories interacted with *eTRS Badge*. This set of 33 interactions absorbs, at least at the meta-category level, any unobserved category differences correlated with concentration or eTRS prevalence. Our findings are largely unaffected by the inclusion of these additional terms.

In each specification above, our estimate of certification's impact on demand is based on the assumption of a particular (linear) parametric relationship between the badge and (a function of) market or seller attributes. We allow for greater flexibility in the way that certification's impact is affected by market and seller attributes in Table S2 in the supplementary appendix, which also provides a more straightforward interpretation of effect magnitudes. When we include interactions of *eTRS Badge* and indicator variables for *HHI* quartiles, we obtain coefficients that imply that the effect of certification is more than twice as large for listings in the lowest (most competitive) *HHI* quartile relative to the highest quartile. When we interact *eTRS Badge* and indicator variables for quartiles of *eTRS Share*, we find that the coefficients on these interaction terms are monotonically decreasing in *eTRS Share* quartile. The effect of certification is 2.5 times higher for listings in low *eTRS Share* versus high *eTRS Share* categories. Finally, we show the interactions of *eTRS Badge* with *Feedback* quartile dummies – the coefficients are decreasing with seller feedback, and the implied effect of certification is over twice as large for low versus high feedback sellers.

Finally, in Table S3 in the supplementary appendix, we repeat our main analyses, employing alternative measures of market concentration based on quantity sold. Our results are insensitive to the particular definitions of market concentration we employ – are findings are virtually unchanged when using quantity-based measures in place of listings.

C. Competitive impact of eTRS badge

The estimates above indicate how a given seller's outcomes improve upon receipt of certification, conditional on her own characteristics and the characteristics of the market in which she competes. It is unclear, however, whether the positive impact of certification on demand represents purchases that otherwise would not have occurred, or whether the increased sales due to certification for a given seller may come at the expense of sales by competitors. Moreover, if it is the case that certification's increase in demand comes at competitors' expense, is unclear which types sellers stand to lose the most when rivals receive certification. For example, if sellers who gain the badge predominantly gain market share from unbadged rivals, then certification programs may bolster market concentration among (differentiated) high quality firms, On the other hand, if sellers who gain the badge draw market share only from badged rivals, this may promote robust competition at the high-quality end of the market. A decisive analysis of the full welfare effects of shifts in market share would require a considerably more detailed model and appropriate data, but our consideration of these issues may help to inform the design of certification institutions, and also indicate useful directions for future work.

We examine the "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 Badge*$_i$ 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, and so forth).

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 Badge* = 0. The coefficient is negative and significant at the 1% level, indicating that a 10 percentage point increase in category-level prevalence of eTRS listings 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.) In specification 2, which presents analogous results for STP matches where *eTRS Badge* = 1, the coefficient on eTRS prevalence is nearly twice as large, indicating an even greater business stealing effect from 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. Thus, while all sellers experience reductions in their sales probability when more competitors are certified, those sellers who are certified themselves are more severely affected.

In specifications 3 – 6, we further disaggregate sellers based on their sales volume in the month prior to listing. In the first pair of specifications we compare the effect of eTRS prevalence on unbadged sellers, further disaggregated based on whether their revenue for the previous three months was above £3000, and in the second pair of specifications we present results for badged sellers, split at the same revenue threshold. In both pairs of results, the coefficient on eTRS prevalence is more negative for smaller sellers, indicating an attenuated effect of business stealing on high-volume sellers. In terms of a percentage impact on sales probabilities, this difference becomes more modest in magnitude once one accounts for the baseline difference in sales probability (0.33 versus 0.28 for small versus large sellers respectively).[19] While the difference between specifications 1 and 2 indicate more competition within the badged population than across the certified versus uncertified, these results on seller size suggest that larger sellers may be more successful at differentiating themselves from their badged competitors. In specifications 7-10, we examine whether the effect of eTRS prevalence differs for high versus low priced items, subdividing the sample based on whether a listing's price is above £14. For both badged and unbadged sellers, the coefficient is more negative for high-priced listings (the sales completion probability is identical (0.29) for both listing types). This finding is consistent with a greater business-stealing effect of certification for transactions where high-priced items are associated with a greater concern over seller misrepresentation or opportunism. These differences in the impact of

[19] The listings included in Table 5's analysis must have variation in *Sale* within a fixed badge status, which yields the differences between these success rates and the STP-sample mean value of .27 reported on Table 1.

rising eTRS prevalence further underscore the differential impact that certification may have on sellers with different attributes.

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 impact of quality certification on demand. 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 £0.89 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 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 new, high-quality sellers. Additionally our analysis suggests that gaining certification has greater value for sellers in markets that are more fragmented. Thus, the incentives provided by certification to improve or maintain quality are greater in more competitive marketplaces. The benefits of certification depend on the degree to which competitors possess certification as well: the incremental value of certification to a seller is highest when there are few certified rivals. These patterns have implications for market design and firm strategy, and are clearly deserving of future empirical and theoretical attention. (Van der Schaar and Zhang (2014) represent one step in this direction.)

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 or 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. By contrast, Yelp, whose paid business subscribers are given the opportunity to choose which reviews to feature prominently, may find that the value of the ability to affect the presentation of quality assessments changes as more competing businesses subscribe to the service.

Our work may be extended in a number of directions. In this paper, we have focused on a demand-side response to certification. But it is possible – indeed likely – that over time eTRS status may induce sellers to enter new categories or increase the number of listings they post. We defer this supply-side analysis to future work.

Finally, while our emphasis in this paper has been on the heterogeneous effects of certification as a function of market conditions, one could similarly analyze how the benefits of other quality signals may vary with industry conditions. Empirically, our setting has the advantage of discrete shifts in certification status that allow us to generate credible estimates of certification's benefits. In future work we hope to develop approaches to extend our work to assess the heterogeneous impact of firm reputation and other quality assurance mechanisms.

7. References

Akerlof, George A. 1970. "The Market for 'Lemons': Quality Uncertainty and the Market Mechanism." *Quarterly Journal of Economics* 84 (3): 488-500.

Arrow, Kenneth. 1972. "Gifts and Exchanges" *Philosophy and Public Affairs* 1(4): 343-67.

Bajari, Patrick, and Ali Hortaçsu. 2004. "Economic Insights from Internet Auctions." *Journal of Economic Literature*, 42(2): 457–86.

Becker, Bo, and Todd Milbourn . 2011. "How Did Increased Competition Affect Credit Ratings?" *Journal of Financial Economics* 101(3): 493-514.

Bolton, Gary, Ben Greiner, and Axel Ockenfels. 2012. "Engineering trust: reciprocity in the production of reputation information," *Management Science,* forthcoming.

Brown, Jennifer, and John Morgan. 2006 . "Reputation in online markets: some negative feedback." Working paper, University of California, Berkeley.

Dini, Federico, and Giancarlo Spagnolo. 2009. "Buying reputation on eBay: Do recent changes help?" *International Journal of Electronic Business* 7(6): 581-598.

Dranove, David, and Ginger Zhe Jin. 2010. "Quality Disclosure and Certification: Theory and Practice." *Journal of Economic Literature* 48(4): 935-63.

Dranove, David, Daniel Kessler, Mark McClellan, Mark Satterthwaite. 2003. "Is More Information Better? The Effects of 'Report Cards' on Health Care Providers," *Journal of Political Economy* 111(3): 555-88.

Einav, Liran, Theresa Kuchler, Jonathan Levin, and Neel Sundaresan. 2013a. "Learning from Seller Experiments in Online Markets." NBER working paper #17385.

Einav, Liran, Chiara Farronato, Jonathan Levin, and Neel Sundaresan. 2013b. "Sales Mechanisms in Online Markets: What Happened to Internet Auctions?" NBER Working Paper #19021.

Elfenbein Daniel W., and Brian McManus. 2010. "A Greater Price for a Greater Good? Evidence that Consumers Pay More for Charity-Linked Products." *American Economic Journal: Economic Policy* 2 (May 2010), pp. 28-60.

Elfenbein, Daniel W., Raymond Fisman, and Brian McManus. 2012. "Charity as a Substitute for Reputation: Evidence from an Online Marketplace" *Review of Economic Studies* 79(4): 1441-68.

Forbes, Silke, Mara Lederman, and Trevor Tombe. 2012. "Quality Disclosure Programs with Thresholds: Misreporting, Gaming, and Employee Incentives," University of Toronto working paper.

Grossman, Sanford J. 1981. "The Informational Role of Warranties and Private Disclosure about Product Quality." *Journal of Law and Economics* 24(3): 461-83.

Hauser, Daniel, and John Wooders. 2006. "Reputation in Auctions: Theory, and Evidence from eBay." *Journal of Economics and Management Strategy* 15, 353-369.

Ho, Daniel E. 2012 "Fudging the Nudge: Information Disclosure and Restaurant Grading," *Yale Law Journal* 122(3): 574-688.

Hui, Xiang, Maryam Saeedi, Zeqian Shen, Neel Sundaresan. 2013. "From Lemon Markets to Managed Markets: the Evolution of eBay's Reputation System." Working Paper, Ohio State University.

Jin, Ginger Zhe, and Phillip Leslie. 2003. "The Effect of Information on Product Quality: Evidence from Restaurant Hygiene Grade Cards." *Quarterly Journal of Economics* 118(2): 409-51.

Jin, Ginger Zhe, and Phillip Leslie. 2009. "Reputational Incentives for Restaurant Hygiene." *American Economic Journal: Microeconomics* 1(1): 237–67.

Klein, Benjamin, and Keith Leffler. 1981. "The Role of Market Forces in Assuring Contractual Performance." *Journal of Political Economy* 89(4): 615–41.

Lewis, Gregory. 2011. "Asymmetric Information, Adverse Selection and Online Disclosure: The Case of eBay Motors." *American Economic Review* 101(4): 1535-46.

Lizzeri, Alessandro. 1999. "Information Revelation and Certification Intermediaries." *RAND Journal of Economics* 30 (2): 214-31.

Luca, Michael. 2011. "Reviews, Reputation, and Revenue: The Case of Yelp.com." Working Paper, Harvard Business School.

Lucking-Reiley, David, Doug Bryan; Naghi Prasad, and Daniel Reeves. 2007 "Pennies from eBay: the Determinants of Price in Online Auctions." *Journal of Industrial Economics* 55(2): 223-233.

Milgrom, Paul, and John Roberts. 1986. "Price and Advertising Signals of Product Quality." *Journal of Political Economy* 94(4), 796-821.

Ramanarayanan, Subramaniam, and Jason Snyder. 2012. "Reputations and Firm Performance: Evidence from the Dialysis Industry." Working Paper, UCLA.

Roberts, James W. 2011. "Can Warranties Substitute for Reputations?" *American Economic Journal: Microeconomics* 3(3): 69-85.

Saeedi, Maryam. 2012. "Reputation and Adverse Selection: Theory and Evidence from eBay." Working Paper, Ohio State University.

Salop, Steven C. 1979. "Monopolistic Competition with Outside Goods." *Bell Journal of Economics* 10(1): 141-56.

Shapiro, Carl. 1983. "Premiums for High Quality Products as Returns to Reputations." *Quarterly Journal of Economics* 98(4): 659-79.

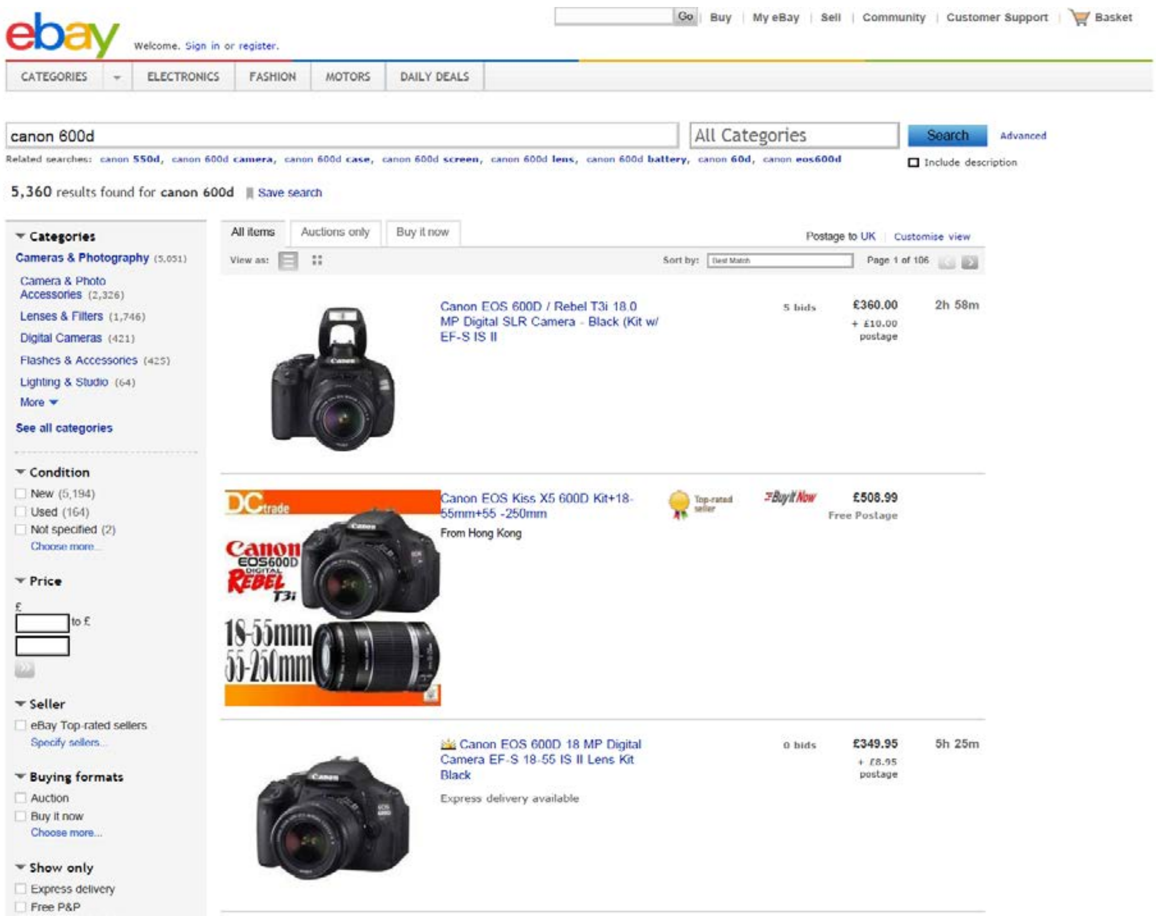
Tadelis, Steven, and Florian Zettlemeyer. 2011. “Information Disclosure as a Matching Mechanism.” University of California - Berkeley working paper.

Van Der Schaar, Miriam, and Simpson Zhang. 2014. “A Dynamic Model of Certification and Reputation.” Working Paper, UCLA.

Wimmer, Bradley S., and Brian Chezum. 2003. “An Empirical Examination of Quality Certification in a Lemons Market.” *Economic Inquiry* 41(2): 279-91.

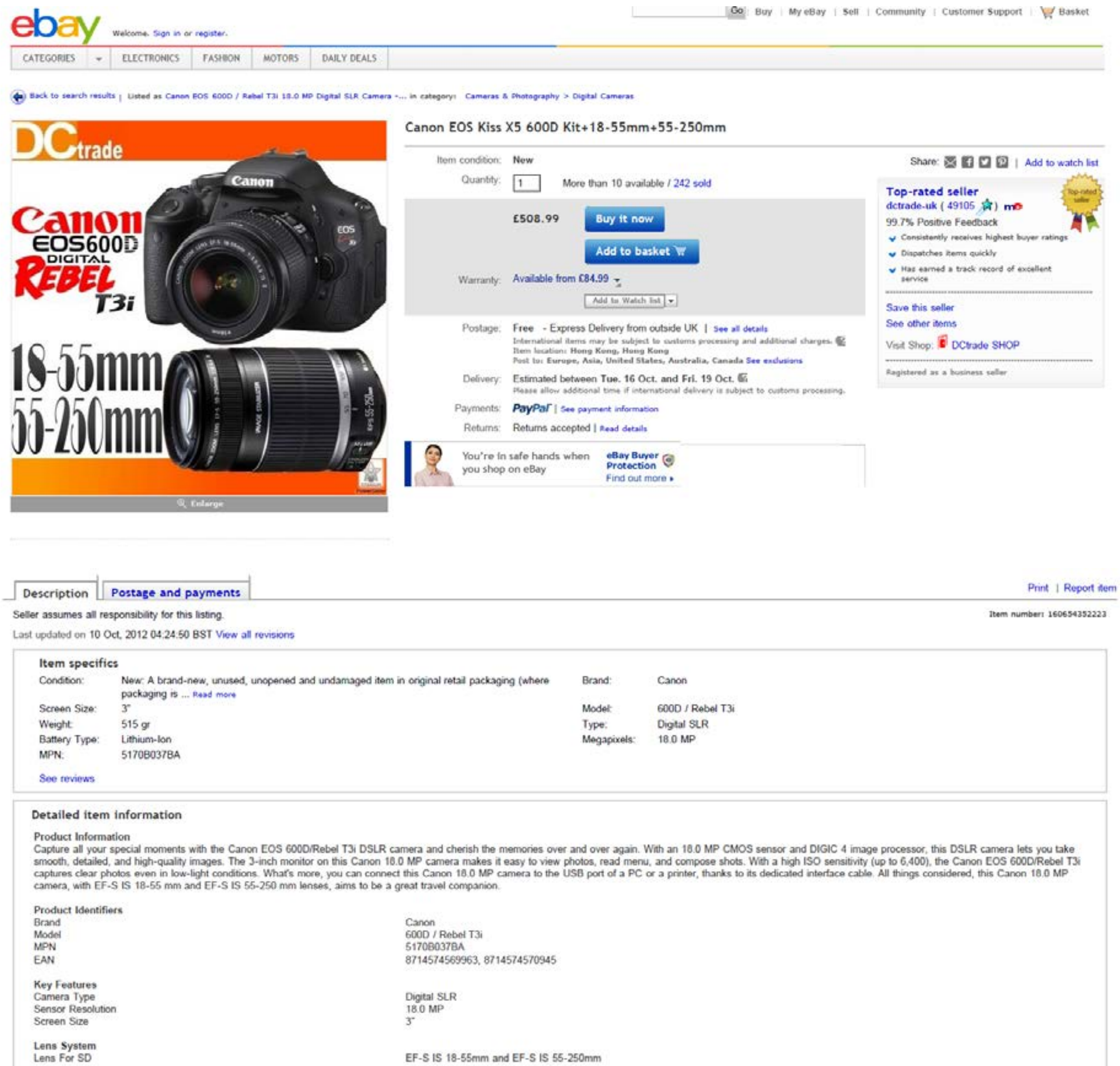
Xiao, Mo. 2010. “Is Quality Certification Effective? Evidence from the Childcare Market.” *International Journal of Industrial Organization* 28(6): 708-21.

Figure 1. The eTRS badge in search results



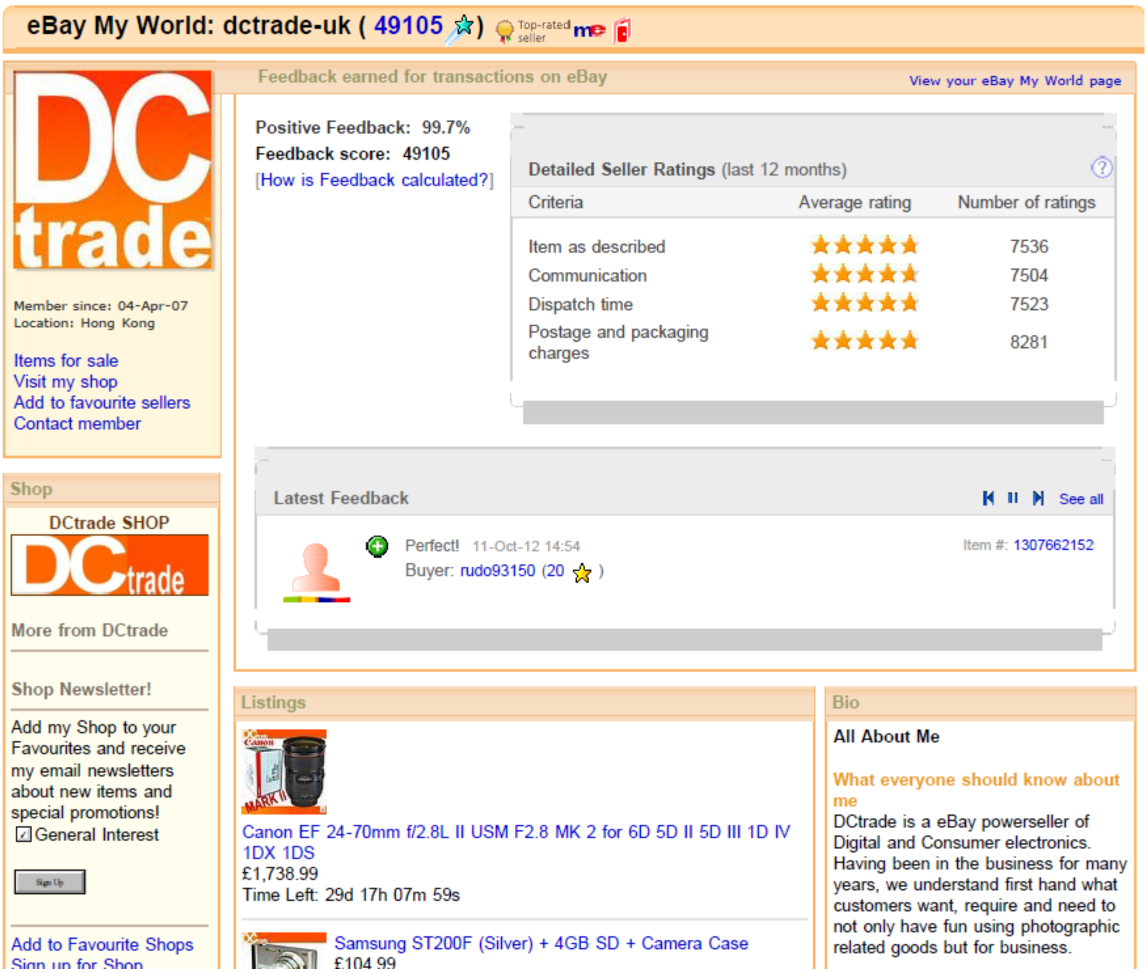
Note: The eTRS badge is found on the second listing in the search results.

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 = 16.3M)					
eTRS Badge (Y = 1)	0.52	1	0.5	0	1
Success (Y = 1)	0.27	0	0.45	0	1
Quantity available	21.82	4	81.27	1	1000
Quantity sold	0.67	0	3.41	0	1000
Offered price	29.1	13.99	48.25	0	3499
Price | Sold (N = 4.5M)	26.32	12.99	43.01	0.99	1117.93
# Impressions	4442.78	1494	9778.59	0	1701247
# Views	41.48	10	132.2	0	26029
Shipping fee	2.59	1.5	5.46	0	6000
# Photos	1.16	1	0.89	0	12
Scheduled length	17.78	10	11.76	1	30
Actual length	15.38	10	11.51	0	47
Category HHI by listings	575.68	267.76	950.77	1.74	10000
Category HHI by quantity	843.39	384.72	1298.68	0	10000
Category eTRS share	0.24	0.21	0.15	0	1
Sellers (N = 22,801)					
# Listings	1364.55	134	10774.18	2	643306
Type-ST matches	95.71	13	1148.84	1	99290
Type-STP matches	168.80	17	3004.44	1	264949
Feedback score	4267.67	1562.02	11204.26	4.64	737378
Transactions in last 3 mo.	538.18	202.11	1456.88	0	87360
Revenue in last 3 mo.	9845.55	3472.40	45989.27	0	4851372
Category listing share	0.03	0.01	0.07	1.31E-06	0.98
Category sold share	0.04	0.02	0.08	4.9E-06	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***	0.0264***	0.0171***	0.0182***	0.0313***
	(0.00166)	(0.00164)	(0.00140)	(0.00166)	(0.00505)	(0.00156)	(0.00162)	(0.00517)
log(*Price*)				-0.313***	-0.312***			-0.294***
				(0.0201)	(0.0200)			(0.0195)
log(*Price*) X *Badge*					-0.00220			-0.00455***
					(0.00148)			(0.00158)
log(*Impressions*)		0.0404***	-0.0253***	0.0374***	0.0374***	0.0584***	-0.0126***	0.0569***
		(0.00280)	(0.00401)	(0.00284)	(0.00284)	(0.00241)	(0.00314)	(0.00250)
log(*Views*)			0.114***				0.123***	
			(0.00333)				(0.00372)	
Match type	STP	STP	STP	ST	ST	STP	STP	ST
Observations	14,070,450	14,070,450	14,070,450	16,281,095	16,281,095	14,070,450	14,070,450	16,281,095
R-squared	0.008	0.016	0.034	0.025	0.025	0.046	0.067	0.054
Number of matches	1,597,977	1,597,977	1,597,977	1,656,439	1,656,439	1,597,977	1,597,977	1,656,439

Notes: Robust standard errors, clustered by seller, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *eTRS badge* is an indicator variable denoting whether the seller had eTRS status at the time a listing closes; *Price* is the listing's posted price; *Impressions* is the number of times a listing was shown to buyers as part of a search result; *Views* is the number of times a listing received a "click-through" and was viewed by a potential buyer. In addition to the listed explanatory variables, the specifications also include the following controls for listing characteristics: the logarithm of shipping fee, whether the listing occurred in the first month of the eTRS program, a quartic time trend, and sets of indicator variables to control flexibly for each of: the listing's duration, its ending day-of-week, and its number of photos. See Appendix Table A1 for the full set of coefficient estimates for specifications 2 and 6. STP match denotes sets of listings from a seller with identical titles, subtitles, and posted prices (but with variation in eTRS status), while ST matches denotes listing sets from a seller with identical titles and subtitles.

Table 3: Interaction of Certification with Market and Seller Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable	Sale	Sale	Sale	Sale	Sale	Sale	Sale
eTRS Badge	0.0203***	0.00928***	0.0310***	0.0309***	0.0209***	0.0480***	0.0423***
	(0.00164)	(0.00225)	(0.00289)	(0.00291)	(0.00376)	(0.00862)	(0.00883)
Listing HHI X *Badge*	-0.00374***			-0.000370			
	(0.00105)			(0.00108)			
log(*Listing HHI*) X *Badge*		-0.00670***			-0.00497***		-0.00460***
		(0.000985)			(0.00105)		(0.000973)
eTRS Share X *Badge*			-0.0477***	-0.0467***	-0.0349***		-0.0343***
			(0.00879)	(0.00902)	(0.00946)		(0.00935)
log(*Feedback*) X *Badge*						-0.00335***	-0.00237**
						(0.00105)	(0.00107)
Observations	14,070,450	14,070,450	14,070,450	14,070,450	14,070,450	14,069,456	14,069,456
R-squared	0.016	0.016	0.016	0.016	0.016	0.016	0.016
Number of STP matches	1,597,977	1,597,977	1,597,977	1,597,977	1,597,977	1,597,653	1,597,653

Notes: Robust standard errors, clustered by seller, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Badge* denotes whether the seller had eTRS status at the time a listing closes, and *Listing HHI* denotes week × leaf category Herfindahl-Hirschman Indices of concentration calculated using sellers' shares of listings. *HHI* is expressed on a 0-10 scale to facilitate interpretation of the coefficients. *eTRS Share* is the percentage of listings in a week × leaf category that are offered by sellers who have the eTRS badge at the time the listing closes. *Feedback* is a seller's eBay feedback score. Coefficients on control variables are omitted to conserve space. All regressions include controls for impressions, the logarithm of shipping fee, whether the listing occurred in the first month of the eTRS program, a quartic time trend, and sets of indicator variables to control flexibly for each of: the listing's duration, its ending day-of-week, and its number of photos.

Table 4: Market and Seller Interactions, with Badge X Meta-Category Fixed Effects

	(1)	(2)	(3)	(4)
Dependent variable	Sale	Sale	Sale	Sale
log(*Listing HHI*) X *Badge*	-0.00844***			-0.00632***
	(0.00107)			(0.00102)
eTRS Share X *Badge*		-0.0460***		-0.0298***
		(0.00854)		(0.00883)
log(*Feedback*) X *Badge*			-0.00313***	-0.00237**
			(0.00104)	(0.00105)
Observations	14,070,450	14,070,450	14,069,456	14,069,456
R-squared	0.016	0.016	0.016	0.016
Number of STP matches	1,597,977	1,597,977	1,597,653	1,597,653

Notes: Robust standard errors, clustered by seller, in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Each model contains interactions between *Badge* and separate dummy variables for each of 33 eBay product meta-categories. *Listing HHI* denotes week × leaf category Herfindahl-Hirschman Indices of concentration calculated using sellers' shares of listings. *HHI* is expressed on a 0-10 scale to facilitate interpretation of the coefficients. *eTRS Share* is the percentage of listings in a week × leaf category that are offered by sellers who have the eTRS badge at the time the listing closes. *Feedback* is a seller's eBay feedback score. Coefficients on control variables are omitted to conserve space. All regressions include controls for impressions, the logarithm of shipping fee, whether the listing occurred in the first month of the eTRS program, a quartic time trend, and sets of indicator variables to control flexibly for each of: the listing's duration, its ending day-of-week, and its number of photos.

Table 5: Impact of Competitors' eTRS Certification on *Sale*

Fixed seller eTRS status	*Badge* = 0		*Badge* = 1	
Specification	(1)		(2)	
eTRS Share	-0.0437***		-0.0702***	
	(0.00852)		(0.0114)	
Observations	6,735,047		9,071,017	
Number of STP-*Badge* matches	894,593		1,171,894	
Seller characteristic:	Small Seller	Large Seller	Small Seller	Large Seller
Specification	(3)	(4)	(5)	(6)
eTRS Share	-0.0530***	-0.0409***	-0.0828***	-0.0559***
	(0.0120)	(0.0136)	(0.0131)	(0.0147)
Observations	2,494,747	3,269,265	3,050,929	6,020,088
Number of STP-*Badge* matches	400,839	407,674	495,566	676,328
Product characteristic:	Low Price	High Price	Low Price	High Price
Specification	(7)	(8)	(9)	(10)
eTRS Share	-0.0377***	-0.0503***	-0.0637***	-0.0773***
	(0.0105)	(0.0108)	(0.0157)	(0.0126)
Observations	3,561,709	3,173,338	4,575,252	4,495,765
Number of STP-*Badge* matches	451,182	443,411	604,103	567,791

Notes: Robust standard errors, clustered by seller, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Specifications 1, 3, 4, 7, and 8 hold fixed *eTRS Badge* = 0 within a match. The other specifications have *eTRS Badge* = 1 for all listings within a match. *eTRS Share* is the percentage of listings in a week × leaf category that are offered by sellers who have the eTRS badge at the time the listing closes. Seller size models (specifications 3-6) split the seller population based on quarterly revenue. Low/High Price models (specifications 7-10) divide the matches by whether the mean price within-match is above or below the sample median. Coefficients on control variables are omitted to conserve space. All regressions include controls for impressions, the logarithm of shipping fee, whether the listing occurred in the first month of the eTRS program, a quartic time trend, and sets of indicator variables to control flexibly for each of: the listing's duration, its ending day-of-week, and its number of photos.

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 the circle.[20] 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:

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

$$q_i = [p - p_i + (\alpha_H - E(\alpha)) + t/N]/t$$

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 *w*s 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.

1

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***	0.0171***	Results continued from left		
	(0.00164)	(0.00156)			
log(Impressions)	0.0404***	0.0584***	Sched. Length = 3 (Y = 1)	0.390***	0.996***
	(0.00280)	(0.00241)		(0.0233)	(0.301)
First month of eTRS	0.00686	0.0104	Sched. Length = 5 (Y = 1)	0.397***	0.996***
	(0.00553)	(0.00682)		(0.0214)	(0.301)
First month of eTRS X Badge	0.00379	0.00218	Sched. Length = 7 (Y = 1)	0.411***	1.000***
	(0.00589)	(0.00684)		(0.0208)	(0.301)
log(Shipping fee)	-0.0147***	-0.0145***	Sched. Length = 10 (Y = 1)	0.443***	1.041***
	(0.00149)	(0.00169)		(0.0207)	(0.301)
Photos = 0 (Y = 1)	-0.0969**	-0.0904**	Sched. Length = 30 (Y = 1)	0.615***	1.233***
	(0.0399)	(0.0373)		(0.0227)	(0.301)
Photos = 2 (Y = 1)	-0.00374	0.00200	Time	-0.000288*	-0.000877***
	(0.00694)	(0.00851)		(0.000157)	(0.000174)
Photos = 3 (Y = 1)	-0.00146	0.00773	$Time^2$	0.000299**	0.000663***
	(0.00792)	(0.0101)		(0.000134)	(0.000154)
Photos = 4 (Y = 1)	0.00634	0.0131	$Time^3$	-0.00167***	-0.00274***
	(0.00894)	(0.0113)		(0.000454)	(0.000523)
Photos = 5+ (Y = 1)	0.0113	0.0209	$Time^4$	0.00251***	0.00357***
	(0.0112)	(0.0151)		(0.000516)	(0.000596)
End on Monday (Y = 1)	0.00505***	0.00407***	Qty. avail. in [2, 4] (Y = 1)	0.0474***	0.179***
	(0.00119)	(0.00115)		(0.00653)	(0.00942)
End on Tuesday (Y = 1)	0.00661***	0.00557***	Qty. avail. in [5, 10] (Y = 1)	0.0750***	0.336***
	(0.00128)	(0.00123)		(0.00815)	(0.0143)
End on Wednesday (Y = 1)	0.000210	0.00111	Qty. avail. in [11, 20] (Y = 1)	0.0924***	0.498***
	(0.00103)	(0.000969)		(0.00782)	(0.0195)
End on Thursday (Y = 1)	-0.00365***	-0.00239**	Qty. avail. in [21, 50] (Y = 1)	0.0863***	0.571***
	(0.00110)	(0.00103)		(0.00902)	(0.0259)
End on Friday (Y = 1)	-0.00801***	-0.00673***	Qty. avail. in [51, 100] (Y = 1)	0.0708***	0.553***
	(0.00101)	(0.000932)		(0.0124)	(0.0332)
End on Saturday (Y = 1)	-0.00832***	-0.00660***	Qty. avail. 101+ (Y = 1)	0.0595***	0.579***
	(0.000964)	(0.000907)		(0.0152)	(0.0405)
			Constant	-0.548***	-1.448***
				(0.0237)	(0.301)
Observations	14,070,450	14,359,591			
R-squared	0.016	0.046			
Number of STP matches	1,597,977	1,630,123			

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

Appendix Table A2: Robustness of Badge Effect

	(1)	(2)	(3)	(4)
Dependent variable	Sale	Sale	Sale	Sale
eTRS Badge	0.0210***	0.0186***	0.0275***	
	(0.00188)	(0.00129)	(0.00281)	
Share of listing time with badge				0.0264***
				(0.00198)
log(*Impressions*)	0.0439***	0.0373***	0.0490***	0.0402***
	(0.00350)	(0.00236)	(0.00521)	(0.00281)
Match type	STP + Listing characteristics	STP + Recent month eTRS change	STP + 20-day window eTRS change	STP
Observations	11,939,804	4,451,912	551,446	14,070,450
R-squared	0.010	0.014	0.019	0.016
Number of matches	1,494,211	678,305	122,932	1,597,977

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 2's notes and provided in Appendix Table A1.

Appendix Table A3: Effects of eTRS Badge on Impressions and Views

	(1)	(2)	(3)
Dependent variable	Log(Impressions)	Log(Views)	Log(Views)
eTRS Badge	0.0924***	0.0440***	-0.00949
	(0.0156)	(0.0133)	(0.00662)
log(*Impressions*)			0.579***
			(0.0112)
log(*Shipping Fee*)	-0.0136***	-0.0199***	-0.0121***
	(0.00516)	(0.00398)	(0.00183)
3-day listing	0.843	1.871***	1.383***
	(0.699)	(0.412)	(0.0446)
5-day listing	0.997	1.870***	1.293***
	(0.698)	(0.411)	(0.0305)
7-day listing	1.143	1.982***	1.320***
	(0.700)	(0.411)	(0.0312)
10-day listing	1.271*	2.035***	1.298***
	(0.697)	(0.410)	(0.0252)
30-day listing	1.634**	2.301***	1.355***
	(0.698)	(0.411)	(0.0407)
Observations	14,070,450	14,070,450	14,070,450
R-squared	0.164	0.177	0.638
Number of matches	1,597,977	1,597,977	1,597,977

Notes: Robust standard errors, clustered by seller, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Among the listing duration variables '1-day listing' is the omitted category. 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.

Supplementary Appendix

Table S1: Within-Match Price Differences

	(1) Price	(2) Price	(3) log(Price)	(4) log(Price)	(5) Price + ship fee	(6) log(Price + ship fee)	(7) Ship fee	(8) log(Ship fee)
eTRS Badge	-0.00133	-0.0287	0.000285	-0.00167	-0.0381	-0.00215*	-0.0368**	-0.0655**
	(0.0355)	(0.0322)	(0.00213)	(0.00146)	(0.0333)	(0.00111)	(0.0172)	(0.0313)
log(*Shipping Fee*)		-0.417***		-0.0298***				
		(0.0512)		(0.00379)				
Observations	31,130,934	31,130,934	31,130,934	31,130,934	31,130,934	31,130,934	31,130,934	31,130,934
R-squared	0.000	0.004	0.004	0.043	0.001	0.004	0.000	0.010
Number of ST Matches	4,311,151	4,311,151	4,311,151	4,311,151	4,311,151	4,311,151	4,311,151	4,311,151

Notes: Robust standard errors, clustered by seller, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All models include the full set of controls listed on Table A1 with the exception of log(Impressions), which is excluded.

Table S2: Market and Seller Characteristics, Divided into Quartiles

	(1)	(2)	(3)
Dependent variable	Sale	Sale	Sale
1st quartile *Listing HHI* X *Badge*	0.0285***		
	(0.00225)		
2nd quartile *Listing HHI* X *Badge*	0.0239***		
	(0.00252)		
3rd quartile *Listing HHI* X *Badge*	0.0244***		
	(0.00176)		
4th quartile *Listing HHI* X *Badge*	0.0134***		
	(0.00372)		
1st quartile *eTRS share* X *Badge*		0.0334***	
		(0.00231)	
2nd quartile *eTRS share* X *Badge*		0.0262***	
		(0.00199)	
3rd quartile *eTRS share* X *Badge*		0.0229***	
		(0.00234)	
4th quartile *eTRS share* X *Badge*		0.0130***	
		(0.00183)	
1st quartile *Feedback* X *Badge*			0.0349***
			(0.00220)
2nd quartile *Feedback* X *Badge*			0.0242***
			(0.00233)
3rd quartile *Feedback* X *Badge*			0.0188***
			(0.00223)
4th quartile *Feedback* X *Badge*			0.0150***
			(0.00478)
Observations	14,070,450	14,070,450	14,070,450
R-squared	0.008	0.008	0.008
Number of STP matches	1,597,977	1,597,977	1,597,977

Notes: Robust standard errors, clustered by seller, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All models include the full set of controls listed on Table A1.

Table S3: Alternative Measures of Market Concentration

	(1)	(2)	(3)
Dependent variable	Sale	Sale	Sale
eTRS Badge	0.0243***	0.0188***	
	(0.00193)	(0.00145)	
Quantity HHI X *Badge*	-0.00280***		
	(0.000565)		
log(*Quantity HHI*) X *Badge*		-0.00316**	
		(0.00136)	
1st quartile *Quantity HHI* X *Badge*			0.0238***
			(0.00733)
2nd quartile *Quantity HHI* X *Badge*			0.0246***
			(0.00254)
3rd quartile *Quantity HHI* X *Badge*			0.0221***
			(0.00181)
4th quartile *Quantity HHI* X *Badge*			0.0186***
			(0.00201)
Observations	14,070,450	14,062,245	14,070,450
R-squared	0.008	0.008	0.008
Number of STP matches	1,597,977	1,597,977	1,597,977

Notes: Robust standard errors, clustered by seller, are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. *Quantity HHI* denotes week × leaf category Herfindahl-Hirschman Indices of concentration calculated using sellers' shares of all items sold. All models include the full set of controls listed on Table A1.