

Quality-Adjusted Consumer Surplus for Markets with Asymmetric Information

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Traditional measures of consumer surplus (CS) have implicitly assumed that the quality expected is the same as the quality that is paid for ex ante. However, when product or service quality cannot be perfectly verified ex-ante by consumers in markets with asymmetric information, and actual quality received may not necessarily equal quality expected, CS would not be precisely measured. This may lead to either over-estimation or under-estimation of the real level of CS, thus misrepresenting the true surplus markets render to consumers. In this paper, we propose a quality-adjusted measure of CS for markets with asymmetric information. We first relax the assumption that consumers always receive the quality they expect ex ante. Second, we leverage expectation-confirmation theory to construct the utility function to derive the proposed quality-adjusted measure of CS.

As an illustration, we estimate the quality-adjusted measure of CS using transaction data from a global electronic marketplace for outsourcing of services. We compare the quality-adjusted measure of CS with the traditional CS measure. While the quality-adjusted measure of CS is shown to yield a smaller level of surplus compared to the traditional measure, the quality-adjusted measure of CS is more predictive of market performance (buyer continuity, market liquidity, and total transaction volume). We also empirically identify the parameters that render the quality-adjusted measure of CS to deviate from the traditional CS measure. While the two CS measures converge at an aggregate level over time, individual service-level differences still persist. Implications for theory and practice are discussed.

Consumer surplus (CS), as an important metric for societal welfare, has long been of interest to economists (J.A. Breslaw and J.B. Smith 1995, J.A. Hausman and W.K. Newey 1995, Alfred Marshall 1920, M. Song 2007, Y.O. Vartia 1983). How to precisely capture CS remains a challenge (I.J. Irvine and W.A. Sims 1998). Important as it is, methods to empirically measure CS are surprisingly scarce, due to lack of precise theory to guide its measurement and limited availability of data. The study of CS traces back to the early 20th century where it was defined as the difference between the maximum price a consumer is willing to pay (WTP) for a product and the actual price paid (p). The literature has mainly focused on demand estimation of a commodity product, in which CS is usually graphically represented by the integral above the equilibrium price and below the demand curve, without substantive consideration for *ex-post* consumer satisfaction. Indeed, Alfred Marshall's (1920) original definition of CS centered on the concept of satisfaction, as his seminal work (Alfred Marshall 1920) stated:

... [the consumer] derives from a purchase a surplus of satisfaction. The excess of the price which he would be willing to pay rather than go without the thing, over that which he actually does pay, is the economic measure of this surplus of satisfaction. It may be called consumer's surplus. [p. 124]

Later Michael Burns (1973) reconsidered Marshall's terminology of CS, and proposed the expression of "gain in utility" to substitute "surplus of satisfaction" to make it measurable. Generally, demand estimation methods are used to infer CS (Minjae Song 2007). However, demand estimation methods may not be useful for highly heterogeneous niche products or idiosyncratic services because those are usually one-time transactions.¹ Also, measurement of CS generally focuses on a "pre-transaction" concept. CS is traditionally measured as $WTP - p$, assuming

¹ Services are customized products that require consumer involvement and interactions with the service provider, and the ultimate quality of the service depends on the interaction (Steven L. Vargo and Robert F. Lusch 2008). Hence, for services that are tied to their providers, CS is contingent upon the provider's quality to a larger degree than commodity products.

quality to be known *ex-ante* (or actual quality is what is expected and paid for). However, in a scenario with pre-purchase information asymmetry, such as global online markets for outsourcing of services, the quality of the product or service the customer receives may deviate from what was expected, due to two reasons. First, the buyer may not have a realistic expectation of the actual product/service quality, leading to a cognitive mismatch of her² expectation and actual quality received. Second, unique products/services are difficult to contract and incomplete contracts lead to the potential for moral hazard. The source of moral hazard is the asymmetric information between the buyer and the seller because seller actions cannot be perfectly observed and hence contracted upon (Bengt Hölmstrom 1979). To make the matter even worse, geographical separation renders a natural remedy to moral hazard – performance monitoring - virtually impossible. For example: imagine a buyer who requests a website development service and is willing to pay \$250 for the website. The request attracts 10 providers with bids ranging from \$100 to \$300. The fact that the chosen provider receives \$200 assumes a \$50 surplus. However, the simple math of deriving \$50 in surplus is not accurate because the *actual* quality of the service may either be better or worse than the *ex ante* expected quality of \$250. More general, a consumer who receives a product that does not meet her expectations suffers a loss of surplus (Christopher Lawton 2008), even if she bought the product at a discounted price lower than her *ex ante* WTP. In such scenarios, the traditional measure of CS may be biased, and even at odds with reality; to calculate the true realized value of CS, a quality adjustment for actual *ex post* quality of the product or service received is needed to reflect economic reality.

While these simple examples of measuring CS convey the limitation of the traditional measure of CS, this limitation may be more systematic. For example, contracts in markets with asymmetric information are based on reputation and trust.

² In this paper, we use “she” to refer to the buyer and “he” the seller.

When buyers and service providers are geographically dispersed, physical monitoring becomes difficult, allowing providers to “shirk”, potentially resulting in moral hazard (WSJ 2008). Incomplete contracts and moral hazard faced by markets with asymmetric information may lead to the problem of sellers not performing according to buyer’s *ex-ante* expectations. Consumer dissatisfaction is common in markets with asymmetric information (P Resnick and R Zeckhauser 2002). Hence, when actual quality received may not perfectly equal quality expected due to variation in consumption experience, the traditional CS measure may misrepresent (either over-estimate but under-estimate) the true surplus markets offer to consumers, thus creating a need for a quality-adjusted measure of CS. Specifically, we derive a measure of CS that takes into consideration the (a) heterogeneity in product/service quality; and (b) *ex-post* consumer satisfaction.

While extant research on CS has not factored actual quality received and *ex-post* satisfaction, expectation confirmation theory (ECT) (Eugene W. Anderson and Mary W. Sullivan 1993, Richard L. Oliver 1977) offers a theoretical basis to adjust the traditional measure of CS. ECT argues that *ex-ante* expectations, coupled with actual quality, lead to *ex-post* satisfaction; the relationship is mediated by positive or negative confirmation between *ex ante* expectations and *ex post* quality. Simply put, when actual *ex post* quality falls below *ex ante* expectations, the consumer is likely to be dissatisfied, thus imposing a negative effect on CS. Accordingly, ECT can be used to derive the utility function to derive a quality adjusted measure of CS, thus allowing us to relax the assumption that customers actually receive what they *ex-ante* expected. We relax the key assumption made in the CS literature that what a consumer receives equals what he expects. While relaxing this key assumption that *ex-ante* expectation does not equate with *ex post* satisfaction is bound to put forth measurement challenges, it is a modest step towards economic reality. Moreover, identifying whether and when the quality-adjusted measure of CS is systematically different from the traditional measure of CS is important in both predicting the

performance of markets with asymmetric information and prescribing implications for increasing CS. In sum, the following research questions have guided our study:

- How should CS be measured in markets with asymmetric information?
- When does the quality-adjusted measure of CS deviate from the traditional measure of CS?
- Does the quality-adjusted measure of CS predict market performance better than the traditional measure of CS?

To answer these research questions, we first derived a quality-adjusted measure of CS to include the buyer's ex post actual quality received. While it is generally difficult to measure CS (Ravi Bapna, Wolfgang Jank and Galit Shmueli 2008), using micro-level data from an online market for the outsourcing of services allowed us to include measures of both *ex-ante* expected service quality and actual *ex-post* service satisfaction. While not readily available in traditional markets, data on past seller quality and consumer satisfaction are usually documented, aggregated and maintained in online markets by third-parties (e.g., marketplace intermediaries) in the form of feedback ratings. Accordingly, these micro-level data on previous service provider quality and ex post consumer satisfaction with the service provided create an opportunity for us to empirically derive a quality-adjusted measure for CS. Furthermore, as online markets for services are vaunted for their benefits to society, this study seeks to empirically quantify the magnitude of their surplus to consumers.

In what follows, we describe our research context of global online markets for the outsourcing of services, and illustrate the limitations of the traditional CS measure. We next review the literature on CS in markets with asymmetric information and integrate the ECT literature. We then derive the quality-adjusted measure for CS, and compare the quality-adjusted to the traditional measure of CS. We find that these two measures deviate systematically and we compare their effects on market performance. We conclude by discussing the study's theoretical implications for CS and practical implications for the design of markets with asymmetric information.

I. Markets with Asymmetric Information: Global Online Markets for Services

In online markets for the outsourcing of services, such as eLance,³ rent-a-coder, and freelancer.com (Thomas W. Malone and Robert J. Laubacher 1998), people can outsource various services, such as website development, graphical design, or creative writing. The potential of these markets was widely touted (Jeff Howe 2006, *Wired* magazine); since their inception, they have been expanding at an astounding pace despite the economic crisis (The Economist 2010). These markets serve as intermediaries for services (buyers post request for proposal (RFP) for services and providers offer bids for services) that help match buyers with service providers across the globe at low search costs (Yannis Bakos 1999). Figure 1 shows a request for bids page posted by the service buyer on a typical online market for services.



FIGURE 1—A SNAPSHOT OF A PROJECT REQUEST IN ONLINE MARKETS FOR SERVICES

In online markets, buyers choose service providers by weighing the expected quality of providers relative to their bids (Rajiv D. Banker and Iny Hwang 2008). Due to information asymmetry, buyers may suffer from adverse selection when trying to shield themselves from the uncertainty involved in selecting providers.

³ As elance.com is the first major online market for services that was widely covered by the press, it has become a synonym for "online markets for services". Please see Malone and Laubacher (1998) for a more detailed description of these markets.

The Bureau of Labor Statistics estimates that more than 30 million people now work as independent professionals in the United States alone, and the dynamics of these online markets have drawn increased attention in the academic literature (e.g., Rajiv D. Banker and Iny Hwang 2008, David Gefen and Erran Carmel 2008, Eli M. Snir and Lorin M. Hitt 2003).

II. Theoretical Background

A. Consumer Surplus

CS has been defined as “the excess of the price which he (the consumer) would be willing to pay rather than go without the thing, over that which he actually does pay” (A. Marshall 1920, p. 124).⁴ The classic definition of CS focused on willingness to pay (WTP), and the actual monetary payment, given a known quality. There has been considerable interest in CS in the literature, and there are several theoretical models to extend the original models (Charles J. Cicchetti and A. Myrick Freeman III 1971, Austan Goolsbee and Amil Petrin 2004, Aviv Nevo 2003, Alan Randall and John R. Stoll 1980, SJ Turnovsky, H Shalit and A Schmitz 1980) along with empirical applications (Ravi Bapna, Wolfgang Jank and Galit Shmueli 2008, Erik Brynjolfsson 1996, Judy Harris and Edward A. Blair 2006).

Alfred Marshall’s theorization of CS focused on a market for a single commodity product. An assumption was made that product quality was “common knowledge”, meaning that every consumer is homogeneous on product quality assessment with full *ex ante* information. Simply put, “what you pay is what you get”. However, for many non-commodity products and services, knowledge about quality may not be common and transferrable; therefore, the fundamental issue the literature has not yet addressed is the simple phrase: “what you pay is not necessarily what you get”.

⁴ As individual CS aggregates to societal welfare for consumers, research on CS gave rise to welfare economics ([Marshall 1920](#)).

CS has been viewed as a criterion for evaluating the societal impact of technology (Lorin M. Hitt and Erik Brynjolfsson 1996), and how much technology helps enhance total societal welfare (Varun Grover and Pradipkumar Ramanlal 1999). Erik Brynjolfsson (1996) examined the contribution of information technology (IT) to CS and found that IT spending generated over \$50 billion in net value and increased economic growth by 0.3% per year in the United States of America. In line with classical economics, their approach to CS was to add up individual surpluses of infra-marginal buyers who paid less than they would be willing to pay (integrating the area under the demand curve between old and new price – before and after an IT investment) (Erik Brynjolfsson, Yu (Jeffrey) Hu and Michael D. Smith 2003, Lorin M. Hitt and Erik Brynjolfsson 1996).

CS has also been measured and estimated with pure-characteristic demand model (Minjae Song 2007) with structural estimation methods developed by Steven Berry, James Levinsohn and Ariel Pakes (also known as BLP, 1995, 2003). Economists also developed other methods. Jerry A. Hausman and Whitney K. Newey (1995) used non-parametric methods and estimated the welfare loss from tax on gasoline (J.A. Hausman and W.K. Newey 1995). When Hicksian demands are unknown, Ian J. Irvine and William A. Sims proposed a measure based on Slutsky compensated demand (I.J. Irvine and W.A. Sims 1998). These approaches are appropriate for explaining the societal impact given market equilibrium of a homogeneous product, but less effective for deriving a precise measure of CS because of two reasons: first, every heterogeneous product or service is idiosyncratic; second and most important, actual consumption experience was not formally considered in the CS literature.

B. Customer Satisfaction and Expectation-Confirmation Theory (ECT)

Customer satisfaction is a *post hoc* evaluation of consumption experience (Richard L. Oliver 1980). The literature has established that two variables –

performance-specific expectation, and expectancy disconfirmation - play a major role in customer satisfaction (Eugene W. Anderson and Mary W. Sullivan 1993, Richard L. Oliver 1977). With virtually no exception, the stream of research on consumer satisfaction has reached the conclusion that “satisfaction is a function of an initial standard and some perceived discrepancy from the initial reference point” (Oliver 1980, p. 460). The literature has also characterized the effects of post-purchase satisfaction, such as complaints and repurchases (L.M. Robinson 1979) and behaviors (M. Fishbein 1967), such as switching (Susan M. Keaveney 1995). Satisfaction was characterized as a utility-based concept in both the economics (Michael E. Burns 1973) and marketing (Eugene W. Anderson and Mary W. Sullivan 1993) literatures. ECT (Richard L. Oliver 1977, R.A. Spreng, S.B. MacKenzie and R.W. Olshavsky 1996) is a well-established theory to explain consumer satisfaction. It posits that the “(dis)confirmation” of a consumer’s pre-purchase expectation of a product is the key to his post-purchase satisfaction.

ECT was used in many areas, such as measurement of customer satisfaction (Vicki McKinney, Kanghyun Yoon and Fatemeh "Mariam" Zahedi 2002), the effect of application service provision on satisfaction (A. Susarla, A. Barua and A.B. Whinston 2003), systems continuance (Anol Bhattacharjee 2001), and business relationships (Dan J. Kim, Donald L. Ferrin and H. Raghav Rao 2009).

Due to the idiosyncratic nature of services, especially specificity, complexity (Eli M. Snir and Lorin M. Hitt 2003) and non-contractibility (Sunil Mithas, Joni L. Jones and Will Mitchell 2008), buyers have *ex-ante* uncertainty about the expected service from the provider, and *ex-post* intractability of the contracted provider’s efforts. A natural outcome is customer’s expectations of service quality being disconfirmed, thereby leading to dissatisfaction; or being confirmed, thereby leading to additional satisfaction. We thus argue that *ex-ante* expectations and *ex-post* satisfaction have important implications for measuring CS.

C. Markets for Services with Asymmetric Information

Today's economy has been characterized as a services economy (Steven L. Vargo and Robert F. Lusch 2008). Research on services, goes back to 18th century when Adam Smith (1961) proposed the term "non-productive economic activities". Later the revolutionary role of services in the industrial economy was conjectured by scholars (Alfred Dupont Chandler 1977, Colin Clark 1983). By reviewing the literature on services, Richard B. Chase and Uday M. Apte (2007) concluded that "service performances cannot be guaranteed since they are generally delivered by human beings who are known to be less predictable than machines" (p. 380). Needless to say, services require intense involvement and interactions, and the evaluation of their performance is multi-faceted. Hence, *ex-ante* uncertainty of service quality is significant, since service providers know more about their own characteristics than buyers who can only infer quality from information signals. The literature has also highlighted the characteristics of services. Compared to commodities, services are idiosyncratic, complex (Eli M. Snir and Lorin M. Hitt 2003), non-contractible (Erik Brynjolfsson and Michael D. Smith 2000), with highly variable quality (Roland T. Rust, Jeffrey J Inman, J. Jia and A. Zahorik 1999) and hence can be viewed as "highly-customized" products. Unlike the purchasing of commodities in online markets that can be easily contracted on product descriptions, conditions, and warranties, services have multiple complex components of *labor* that cannot be perfectly described (M Spence 1973), nor can they be easily contracted (such as the efficiency of a customized website). Still, the proposed quality-adjusted measure of CS applies to both services and products.

III. Measure Development

The traditional measure of CS makes the assumption that *ex-ante* quality expectation carries over. We argue that in markets with asymmetric information,

what a consumer expects may differ from what the consumer actually receives. Based on Marshall's (1920) definition of CS, we derive an *ex-post* utility-based measure of CS with two important features: First, we differentiate *ex-ante* quality expectation (q_j) and *ex post* delivered service quality (q_j'). Second, following ECT, we incorporate the effect of disconfirmation of expectation and asymmetric disconfirmation to construct the utility function, in order to capture a consumer's actual experience with the service received. We use the following notations:

TABLE 1—NOTATIONS

<i>Variable</i>	<i>Description</i>
\underline{V}	Buyer's willingness to pay (lower bound)
\overline{V}	Buyer's willingness to pay (higher bound)
\bar{q}	Highest quality a provider can perform the service
\tilde{q}	Acceptable provider quality
q	A buyer's <i>ex-ante</i> quality expectation of a provider
q'	A buyer's <i>ex-post</i> quality assessment of a provider
p	Contract price
$U()$	A buyer's utility function

A. *Quality-adjusted Measure of Consumer Surplus*

The literature has overlooked the fact that even if a consumer under-or over-paid for a product or service, she may still suffer a loss of surplus due to post-purchase dissatisfaction or reap an extra surplus due to unexpected satisfaction. Thus, measuring CS with the difference between *WTP* and price may not be precise because the assumption in the literature that the service or product a consumer receives is the same level of quality as what she expects and paid for may not hold. This suggests two measures of quality: expected quality versus actual quality and *ex-ante expected utility* versus *ex-post actual utility*. However, the literature mainly focuses on *ex-ante expected utility* of a known quality assuming that *ex-ante* quality is equal to *ex-post* quality. In sum, we extend extant research that has focused on price with no substantive considerations for heterogeneities of product or service

service to be offered by provider j , it can only be an expected value, it is possible to approach V_j as the buyer's WTP for the service performed by provider j .

Because WTP is an *ex ante* concept, Equation [1] can only precisely measure CS if a consumer would be willing to pay the same amount V_j when she received the service (or product). The assumption is prone to be violated when the actual quality q_j' is susceptible to deviate from expected quality q_j .

Thus, it is reasonable to argue that a buyer's WTP is tied to provider quality (q_j), with the assumption that buyers have the same sensitivity about WTP per quality. The literature has either made the linearity assumption (Banker and Hwang 2008), or a concave functional assumption used in utility theory (P.C. Fishburn 1970) and the satisfaction literature (Richard L. Oliver 1980). Therefore, without any assumptions, the general form of traditional measure of CS becomes:

$$(2) \quad CS_j = V(q_j) - p(q_j)$$

And the *ex-post* quality-adjusted measure of CS is given by:

$$(3) \quad CS_j' = V(q_j') - p(q_j)$$

Since we seek to reflect economic reality, we need to consider an appropriate form for the utility function with regard to expected or experienced quality. Among many studies, Banker and Hwang (2008) used a linear formulation for the utility function. The limitation of a linear functional form is that it assumes that each unit of increase in quality will result in the same amount of utility increase without decrease in marginal utility. ECT provides the rationale for deriving a monotonically increasing and concave function to represent risk-averse buyers.

According to the analytical framework of Anderson and Sullivan (1993), it is *ex-post* perceived quality (q') and the relative size between expectation of quality q and q' that determines overall satisfaction. ECT predicts that the buyer's positive or negative confirmation, coupled with expected performance, determines her

satisfaction level. We incorporate the ECT logic to adjust CS to reflect reality. As per ECT, we propose integrating ex post confirmation/disconfirmation for the CS model to reflect the buyer's actual utility. Another important aspect of ECT discussed in the literature is asymmetric disconfirmation. As prospect theory (Daniel Kahneman and Amos Tversky 1979) would argue, people place more emphasis on losses than gains. Similarly in the literature on satisfaction (Eugene W. Anderson and Mary W. Sullivan 1993), quality that falls below expectations has a greater impact on satisfaction than quality that exceeds expectations. Thus, we construct a measure that would reflect smaller effect of positive confirmation (when $q' > q$) relative to negative confirmation (when $q' < q$). Thus, a monotonically increasing and concave function is suitable to represent the WTP function.

With a non-linear concave utility formulation and asymmetric disconfirmation, we follow Rust et al. (1999) and Anderson and Sullivan (1993), assuming that utility is a function of expected quality is continuous, twice differentiable, monotonically increasing and concave. The assumption implies that consumers are risk-averse, and that consumers suffer more from not having their expectations met than exceeding their expectations. This assumption is borne out by abundant empirical evidence in the satisfaction and service quality literature (Eugene W. Anderson and Mary W. Sullivan 1993, W.S. DeSarbo, L. Huff, M.M. Rolandelli and J. Choi 1994, J. Jeffrey Inman, James S. Dyer and Jianmin Jia 1997, R.T. Rust, A.J. Zahorik and T.L. Keiningham 1995). A commonly used functional form that meets the assumption is a log utility function⁵: $V(q_j) = v_0 + v_1 \cdot \ln(q_j)$, where v_0 is a constant that indicates the reservation utility, and v_1 is a constant that indicates the sensitivity to service quality. Therefore:

$$(4) \quad CS_j = v_0 + v_1 \cdot \ln(q_j) - p_j$$

⁵ Other commonly used quasi-linear functions include quadratic utility functions.

Equation [4] is what the literature usually assumes, which we herein denote as the traditional measure of CS. However, since *ex-ante* quality may not carry over because of asymmetric information (buyer choosing the wrong service provider) and moral hazard (provider slacking off after contracting), and the actual service received maybe either worse or better than the *ex-ante* service quality expectation, we construct the following adjusted measure for CS:

$$(5) \quad CS_j' = v_0 + v_1 \cdot \ln(q_j') - p_j$$

Equation [5] is the general form of quality-adjusted measure for CS, denotes as the quality-adjusted measure of CS. In practice, when a buyer posts an RFP, it is plausible to assume that she has *a priori* valuation (or WTP) (e.g. buyer is willing to pay \$250 if the provider delivers a website of a reasonable quality level). This valuation is usually in the form of a budget (Eli M. Snir and Lorin M. Hitt 2003), which captures a range of values a buyer is willing to pay for a given service. This *ex-ante* WTP could have an upper and lower bound due to quality variations. Therefore, we make a second assumption that a buyer's posted budget indicates her willingness to pay for a service of a certain level. The upper bound of budget assumes a fully satisfying expected quality, while the lower bound of budget assumes an acceptable level of expected quality; the buyer is willing to pay zero if the provider has the lowest possible quality on the marketplace.

We denote \bar{V} as the WTP for the service with fully satisfying quality (i.e., the quality that achieves the highest WTP for the buyer). It is rational to assume that the buyer's upper bound of WTP \bar{V} can either be tied to the highest quality a provider can have (\bar{q}), or the average provider quality on the marketplace (\tilde{q}). We pick \bar{q} to illustrate the measurement development (in reality any meaningful value for the satisfying quality can be used). By the same token, we argue that the lower bound of WTP \underline{V} would correspond to a lower but acceptable quality on

the marketplace, \hat{q} (the same also applies here that any meaningful value for acceptable quality can be plugged in). And we assume that any buyer would not be willing to pay anything for a lowest quality \underline{q} of the marketplace, and buyers are homogenous in terms of sensitivity to quality. Therefore, we have the following constraints: $\bar{V}_j = v_0 + v_1 \cdot \ln(\bar{q})$ and $\underline{V}_j = v_0 + v_1 \cdot \ln(\hat{q})$. For each service, we derive $\bar{V}_j - \underline{V}_j = v_1 \cdot \ln\left(\frac{\bar{q}}{\hat{q}}\right)$ and to consolidate (derivation omitted for brevity):

$$(6) \quad CS_j = \bar{V}_j + \frac{(\bar{V}_j - \underline{V}_j)}{\ln\left(\frac{\bar{q}}{\hat{q}}\right)} \cdot \ln\left(\frac{q}{\bar{q}}\right) - p_j$$

where q_j is the buyer's expectation of provider j 's quality; CS_j is expected CS.

If we adjust for quality, similarly we can derive a quality-adjusted CS measure:

$$(7) \quad CS_j' = \bar{V}_j + \frac{(\bar{V}_j - \underline{V}_j)}{\ln\left(\frac{\bar{q}}{\hat{q}}\right)} \cdot \ln\left(\frac{q'}{\bar{q}}\right) - p_j$$

Compared with existing measures, the proposed quality-adjusted measure of CS takes into consideration the *actual* service provided and the *ex-post* satisfaction, thus integrating the actual value the service renders to a buyer. Besides, the quality-adjusted measure of CS has face validity by capturing economic reality (potential for dissatisfaction or extra satisfaction). Besides services, this measure is expected to generalize to products and commodities since *ex-ante* expectation of product quality and *ex-post* satisfaction with the product applies to products.

B. Comparing the Performance Effects of the Two CS Measures

Since CS captures the extra utility a buyer derives from a product or service, to test the predictive power of the quality-adjusted measure of CS relative to the traditional CS measure on *market performance*. We identify three indices of

market performance: *buyer continuation* (whether a buyer continues posting RFPs after the first service), *market liquidity* (total amount paid after the first service), and *total transaction volume* (total number of RFPs posted after the first service).

Consumer retention is a key driver of consumer lifetime value and profitability (S. Gupta and V. Zeithaml 2006). Understanding the effect of the two competing CS measures on market performance can shed light on the relative predictive power of the quality-adjusted CS measure. Also, these effects can be seen as the criterion variables that can compare the quality-adjusted versus the traditional measure of CS. Since the quality-adjusted measure of CS includes post-purchase satisfaction and is likely to capture whether the buyer is satisfied with the service and is likely to continue posting requests for services in the market, we propose:

H1a: The quality-adjusted measure of CS better predicts market performance: (a) buyer continuation, (b) market liquidity, (c) transaction volume, than the traditional measure of CS.

The deviation in ex-post quality from ex ante expected quality leads to a difference between the quality-adjusted CS from the traditional measure of CS, which leads to a difference between the effects of the two measures of CS (ΔCS).⁶

$$(8) \Delta CS = CS - CS' = V(q') - V(q)$$

We expect ΔCS to further predict market performance. As derived earlier, ΔCS lies in the relative level of *ex-ante* quality expectation versus *ex-post* quality assessment. The difference equals the amount of additional *ex-post* satisfaction or dissatisfaction due to either positive or negative confirmation (utility gain or loss). Accordingly, the deviation indicates additional gain or loss of CS resulting from either extra ex post positive or extra negative buyer utility relative to ex ante utility.

H1b: The difference between the quality-adjusted and the traditional CS measure (ΔCS) will be positively associated with market performance: (a) buyer continuation, (b) market liquidity, (c) transaction volume.

⁶ In what follows, we use ΔCS to denote “*difference between the quality-adjusted measure and traditional measure of CS*”.

C. When Quality-Adjusted CS' Deviates from Traditional CS

The quality-adjusted measure of CS not only helps predict market performance, but it also has implications for the design of markets with asymmetric information. As ΔCS is the amount of utility (satisfaction) gain or loss due to ex-ante expectation of service/product quality being positively or negatively confirmed ex post, identifying what leads to ΔCS can shed light on how different parameters may have an effect on ex post gain or loss of utility. We propose four predictors of ΔCS : *buyer experience*, *repeat transactions*, *global labor arbitrage*, and *language barrier* that cover aspects of the buyer (buyer's experience in the market), service provider (repeat transactions with a service provider), global market (global labor arbitrage), and friction between buyers and service providers (language barrier).

BUYER EXPERIENCE

As buyers accumulate experience in the market, they learn to increase their CS, and at the same time have more realistic expectations of service quality. First, as Nicholas Carr (2003) argues, in markets with asymmetric information, bid evaluation is costly. Therefore, when multiple bids are available, finding the provider that would offer the highest CS becomes a formidable task. Experienced buyers are more comfortable in awarding contracts to low bidders with fair quality. Second, experienced buyers who have dealt with many service providers before are more likely to incur lower evaluation costs and more effectively and efficiently evaluate all bids to make an informed decision. These reasons suggest that more experienced buyers would have higher *ex-post* utility and thus higher ΔCS .

REPEAT TRANSACTIONS

Studies found that buyers tend to be more willing to select providers with whom they transacted before (David Gefen and Erran Carmel 2008) because they are perceived to have lower transaction costs. From the buyer's perspective, if she is

satisfied with a provider's performance, she is likely to continue using the provider. Subsequent transactions are likely to be smoother as the provider knows what the buyer needs, and thus can finish the service faster. We expect repeat transactions (versus first-time or one-time transactions) to be positively associated with ΔCS .

GLOBAL LABOR ARBITRAGE

Global labor arbitrage is an economic phenomenon where, as a result of the removal of barriers to international trade, jobs move to nations where the cost of labor is relatively cheap. This phenomenon was observed by the New York Times (Stephen S. Roach 2004): "Under unrelenting pressure to cut costs, American companies are now replacing high-wage workers here with like quality, low-wage workers abroad. With new information technologies allowing products and now knowledge-based services to flow more easily cross borders, global labor arbitrage is likely to be an enduring feature of the economy." Global labor arbitrage affects buyers' decisions since buyers are more likely to choose a service provider from poorer country to take advantage of labor arbitrage, thus increasing the buyer's CS. From a utility perspective, the valuation of \$1 dollar varies across people. The utility a service provider can derive from a certain monetary amount also depends on the purchasing power of that amount. Since online markets for the outsourcing of services are global, and services in these markets mostly involve "deliverables" which are easily tradable across borders, offshoring begins to comprise a large portion of total transactions. Gefen and Carmel (2008) found that buyers tend to choose providers from poorer countries; their argument is that for the same amount of monetary award, buyers would expect service providers from poorer countries to reap higher producer surplus and work harder. Building on their logic, we argue that the purchasing power of service provider increases ΔCS because providers from poorer countries are likely to work harder because they have a higher valuation of a given monetary award.

LANGUAGE BARRIER

Language barrier is a major issue on global online markets since effective communication relies on good command of a common language. People from the same country usually can communicate ideas better. Accurate usage of words can eliminate ambiguity, reduce communication costs, and avoid redundant work. Since English is the primary language in global online markets, if both parties fluently speak English would determine whether the service requirements can be effectively communicated. Therefore, we would expect language barrier to be negatively associated with buyers' *ex-post* utility resulting in lower ΔCS .

IV. Methodology

A. Data Description

Our research context is an active global online market for the outsourcing of services where buyers connect with service providers. The online marketplace has around 3 million active users, over \$100 million total transaction volume and over 1.5 million projects contracted and awarded by the end of March 2012.

B. Sample and Integrated Datasets

Our samples come from two archival sources. First, transaction data consisting of a sample of 159,748 RFPs of 38,315 buyers, which took place between February 4, 2004 and September 24, 2010, was obtained from the online market with MySQL query. The outsourcing services were across ten project categories. The data in the sample met the following three criteria:

- (1) Virtually all (>95%) projects had a pre-specified budget (with lower bound and upper bound), which was used as proxy for *ex-ante* WTP.

- (2) For all projects, the provider has at least one feedback rating from past projects, and the buyer left a feedback for the provider for overall service performance.
- (3) All projects were contracted at the winning provider’s bid amount and there were no disputes over the service. Disputed projects consist <3% of all projects.

Second, we obtained the PPP adjusted GDP per capita indices and official language data from the CIA World Factbook⁷, which is widely used in the literature (David Gefen and Erran Carmel 2008). We also obtained PPP data from the International Monetary Fund⁸ and the World Bank⁹ to amend the CIA World Factbook data because PPP data were not available in the CIA World Factbook. We compared indices from the three data sources to ensure consistency (Table 3). We combined the PPP-adjusted GDP data and English-speaking country data with the first dataset. Buyers and providers are from 213 countries or regions, and the English language is the official language for 83 countries or regions.

TABLE 3—SUMMARY STATISTICS OF RELEVANT VARIABLES (N=159, 730)

<i>Variable</i>	<i>Mean</i>	<i>Std. Dev.</i>
Budget (higher bound)	316.000	364.09
Budget (lower bound)	69.358	138.70
Ex-ante average rating	9.841	0.37
Ex-post rating	9.838	0.91
Contracted Price	136.660	245.51

C. Empirical Task 1: Estimating the Level of CS

OPERATIONALIZATION OF CS MEASURES

As explained in Section III, Equations [6] and [7] are the general forms of the proposed quality-adjusted measure of CS. For empirical tractability, we employed

⁷ CIA World Factbook: <http://www.cia.gov/cia/publications/factbook/geos/ae.html/>.

⁸ International Monetary Fund, World Economic Outlook Database. 2010 data.

⁹ World Development Indicators database, World Bank - 29 September 2010

several proxies for our variables. Similar to Anderson and Sullivan (1993), we used feedback ratings to capture service quality. We use the average rating of the provider received in the market as a proxy for *ex-ante* expectation of quality q , and use the rating the buyer left for him for a service indicating his performance in that specific service, q' . Similar to Anderson and Sullivan, the ratings are on a discrete 1-10 interval scale (1 indicates lowest quality and 10 highest quality). For WTP, the literature has used “maximum bid price” as a proxy (Ravi Bapna, Wolfgang Jank and Galit Shmueli 2008). The main difference between maximum budget and maximum bid is that the latter is the actual amount the buyer pays for the service, while the former reveals *ex ante* WTP. Practically, the service provider can bid over the maximum budget, thus leading to negative CS. The budget is chosen as a proxy for WTP since it not only reveals the amount the buyer is willing to pay, but it also affects the amount providers bid to offer for the service. Although either deflating or inflating the budget could potentially be the buyer’s strategic decision to maximize CS, we argue that either choice is not ideal for buyers. As per our debriefing with several respondents after a survey, all buyers are aware that posting an inflated upper bound of budget would attract higher bids, which works against their intention to reap a higher CS; posting a low budget would result in fewer or no bids. Therefore, rational buyers are motivated to post their true WTP.

To make sure that our results are not dependent on the values we choose as acceptable service quality level, we experimented with different values, including using the lowest rating (most liberal), mid-point of the scale, and a high scale (most conservative) as acceptable service quality level (realistically any value between 1-10 may be acceptable service quality), and the highest possible rating (10) as highest quality. In the case of a mid-point (5) denoting acceptable quality, measures of CS can be simplified to:

$$CS_j = \bar{V}_j + \frac{(\bar{V}_j - V_j)}{\ln 2} \cdot \ln \frac{q_j}{10} - p_j \text{ and } CS_j' = \bar{V}_j + \frac{(\bar{V}_j - V_j)}{\ln 2} \cdot \ln \frac{q_j'}{10} - p_j.$$

Table 4 presents the summary statistics for the two measures of CS for all projects and different types of projects. The liberal value for acceptable quality ($\hat{q}=1$) yields a higher bound estimate of \$177 (STD=\$192) per project with the traditional measure of CS, and \$176 (STD=\$193) per project with the quality-adjusted measure of CS. With a conservative value for acceptable quality ($\hat{q}=9$), each project has a lower bound of \$137 (STD=\$356) for the traditional measure of CS and \$94 (STD=\$1,147) for the quality-adjusted measure of CS. Moreover, based on Table 4, technical projects which are presumably more complicated than other projects, have a higher difference between the traditional measure and quality-adjusted measure of CS, indicating that for technical projects, actual CS is more likely to deviate from ex ante expected CS, since *ex-post* quality assessment is more likely to deviate from the *ex-ante* quality expectation.

TABLE 4—TWO MEASURES OF CS WITH DIFFERENT ACCEPTABLE QUALITY & PROJECT TYPES

	Obs.	$\hat{q}=1$	$\hat{q}=5$	$\hat{q}=9$
<i>Panel A. All projects sample</i>				
CS	159,730	177.4 (192.4)	172.9 (192.9)	136.9 (356.1)
CS_adj	159,730	175.5 (192.7)	166.4 (240.2)	94.4 (1147.3)
Paired <i>t</i> -test: (H_0 : CS_adj=CS)		-14.3***	-14.3***	-14.3***
<i>Panel B. IT projects sample</i>				
CS (IT)	80,076	182.3 (219.7)	177.2 (219.5)	136.7 (390.7)
CS_adj (IT)	80,076	179.5 (219.9)	167.9 (279.7)	75.0 (1382.9)
Paired <i>t</i> -test: (H_0 : CS_adj=CS)		-12.2***	-12.2***	-12.2***
<i>Panel C. Creative Writing projects sample</i>				
CS (Writing)	21,627	175.4 (137.8)	171.5 (140.6)	139.8 (274.1)
CS_adj (Writing)	21,627	174.5 (137.3)	168.6 (151.9)	120.8 (544.1)
Paired <i>t</i> -test: (H_0 : CS_adj=CS)		-4.74***	-4.74***	-4.74***
<i>Panel D. Design projects sample</i>				
CS (Design)	41,411	165.6 (162.4)	161.7 (165.1)	130.5 (358.8)
CS_adj (Design)	41,411	164.7 (163.4)	158.9 (193.6)	112.5 (823.3)
Paired <i>t</i> -test: (H_0 : CS_adj=CS)		-4.18***	-4.18***	-4.18***
<i>Panel E. Hold-out sample</i>				
CS (10% dropped ¹⁰)	143,756	157.5 (117.5)	154.1 (117.0)	127.0 (153.8)
CS_adj (10% dropped)	143,756	156.6 (118.5)	151.1 (133.2)	107.3 (471.0)

Note: *** significant at the 0.01 percent level.

¹⁰ Top and lower 5% (based on project size proxied by average bid price) dropped.

Figure 3 has three implications for CS in markets with asymmetric information. First, over time, CS has been increasing, indicating that the market is functioning well as the market matures (when market size increases), validating Joel Waldfogel’s intuition that through the proliferation of service providers, buyer satisfaction will be enhanced (2007, p 102). Second, over time, Δ CS decreases, indicating that buyers, on average, are getting more satisfied with services. Third, the market is not fully correcting the bias since we observe a large variance of Δ CS over time. Therefore, it is important to examine under what scenarios the quality-adjusted CS is susceptible to deviation from the traditional CS measure.

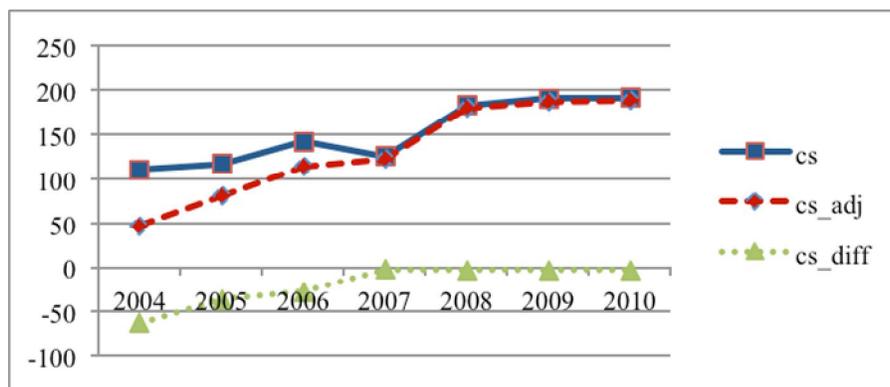


FIGURE 3—TREND OF CS BY YEAR

We employed paired *t*-tests to examine the difference between the mean of CS with the two measures.¹¹ As Table 4 shows, on average, across all services, the traditional CS measure consistently yields a significantly higher surplus than the quality-adjusted CS measure. The results indicate that, although these two measures yield a qualitatively comparable level of CS, the traditional measure is still systematically biased toward inflating the level of CS with all paired *t* tests ($p < 0.0001$ level). Also it should be noted that some projects are highly satisfactory, thus allowing buyers to reap extra CS while others are less than satisfactory thus buyers suffer from a loss of CS. However, at the aggregate level, positive and

¹¹ To test whether the CS level changes significantly when potential outliers are dropped from the analysis, we analyzed the holdout samples with top and lowest 5%. The result is shown to be robust to potential outliers.

negative terms cancel out. If we look closely at the data, we find that, for services with more negative confirmation (e.g., the 1st quintile), the traditional measure of CS is significantly higher than the quality-adjusted CS ($\Delta CS = -\$27$, $STD = \$256$). For projects with positive confirmation (e.g., 5th quintile), the traditional measure of CS is significantly higher than the quality-adjusted CS ($\Delta CS = 24$, $STD = 107$). Finally, given that the average bid price for a project is \$160 and the average winning bid is \$137, the level of CS (\$94-\$176) is surprisingly high (~69%-128% of the winning bid price), indicating notable economic effects of the CS level.

D. Empirical Task 2: Effects and Predictors of Consumer Surplus

VARIABLES DEFINITION AND MEASURES

Dependent Variables. In the effects model, we examined the level of CS on the three dimensions of market performance:

Buyer Continuity: The buyer's continuity in the market was measured with a binary variable indicating whether the buyer posted any new projects after the first project. A satisfied buyer is likely to post projects on the market again.

Market Liquidity: It was measured with a continuous variable capturing the total amount of money paid on the market by the buyer besides the first project. We employed natural logarithmic transformation for the variable to achieve a less skewed distribution. We denote the transformed variable as $\ln(sub_payments)$.

Transaction Volume: It was measured with a discrete variable capturing the total number of subsequent projects the buyer sought on the market. We employed a natural logarithmic transformation for transaction volume to achieve a less skewed distribution. We denote the transformed variable as $\ln(sub_projects)$.

In the predictor model, the dependent variable is ΔCS . ΔCS (cs_diff) was measured by subtracting the quality-adjusted measure by the traditional measure

we derived in Equation (8): $CS_diff = (\bar{V}_j - V_j) \cdot \ln \frac{q_j'}{q_j}$. We employed a natural

logarithmic transformation for this variable to achieve a less skewed distribution.

TABLE 5—DESCRIPTION AND MEASUREMENT OF CONTROL VARIABLES

Project Control Variables

Project Size: It is harder for providers to estimate the cost for finishing a larger project since project size is associated with uncertainty, therefore the bid prices would be more dispersed than smaller projects, offering buyers the chance to reap a higher surplus. Project size was measured with natural logarithmic transformation average bid price for a project. Although different proxies may be used, such as the length of a project and project client value (budget), we employ the proxy used by Snir and Hitt (2003).

Project Category: Different categories of projects may have different levels of price and CS. Different project category might have either a direct or indirect effect on CS. Project Category was coded into three dummy variables - Writing, Design and Data Entry. We set IT projects as the base group, and the effects of all three variables are therefore relative to IT projects.

Non-public Project is likely to be associated with higher average prices because it rules out the low quality bids as Snir and Hitt (2003) described, which are likely to be lower. Non-public Project (*non_public*) was measured with a binary variable indicating whether a project is private (not open to the public).

Featured Project may enhance *ex-post* satisfaction because featured projects are highlighted in the e-market, thus *ceteris paribus*, it draws more providers than non-featured ones, similar to other markets (Angelika Dimoka, Yili Hong and Paul A. Pavlou 2012). Featured project (*featured*) was measured with a binary variable indicating whether a project is *featured* (with a “*featured merchant tag*”).

Trial Project could affect difference in CS measures since high quality service providers may not want to bid on trial projects, resulting in a set of lower quality bids. Trial Project (*trial*) was measured with a binary variable indicating whether an RFP listing is a trial listing.

Project Description Length can be either positively or negatively associated with *ex-post* satisfaction, longer descriptions could be related to higher production cost since it might be associated with more tasks; yet, more detailed descriptions entail less contract cost since the details mitigate follow-up communication costs. It was measured as the total number of words in the buyer’s RFP.

Project Duration may have a negative effect on CS since the service provider may shirk when more time is given for a project, leading to *ex-post* dissatisfaction. Project Duration (*length*) was measured with the number of days a provider estimates for finishing the project.

Winning Bid (bid) was measured with the dollar amount of the winner provider’s bid in a project.

Market Control Variables

Market Maturity: Market maturity is defined as number of days since the market is open to the public. Market maturity can affect CS since a better-regulated market may facilitate the service buyers to find better quality providers; and also, more providers join the marketplace as time goes by, which might increase the expertise variety, and increase *ex-post* satisfaction (Joel Waldfogel 2007).

RFP Duration: We controlled for the role of RFP duration on average price and winning bid. The literature has shown a positive association between duration and the final prices (David Lucking Reiley, Doug Bryan, Naghi Prasad and Daniel Reeves 2007, Mikhail I. Melnik and James Alm 2005). The longer the RFP lasts, the more likely it is viewed by more service providers, thus more supply drives down average price and winning bid amount. RFP (*duration*) was measured with the number of days the RFP was alive.

Number of bids on a RFP was measured with the total number of bids received in a given RFP for a project. We employed natural logarithmic transformation for the variable to achieve a less skewed distribution. We denote the transformed variable as $\ln(\text{number_bids})$.

Other Control Variables

Institutional Buyer: Whether a buyer is an institutional buyer (versus an individual buyer) might affect *ex-post* satisfaction because institutional buyers may have more experience and more realistic expectations. It was measured with a binary variable indicating whether a buyer was an individual or an institution.

Same Country: whether the buyer and the provider are from the same country may affect frictional costs, which negatively affects *ex-post* satisfaction. It was measured with a binary variable if both are from the same country.

Buyer Tenure might be related to his perceived reliability; thus it is included as a control variable.

Provider Rating is an indicator of provider quality, thus is included as a control variable.

Provider Rating is measured with a continuous variable from 1-10. We used an algorithm to retrieve the rating that the buyer observes for the provider when they contract on the service.

Feedback Left (buyer’s satisfaction with the specific project was measured with an interval variable from 1-10.

Predictor Variables

Buyer Experience was measured with the number of projects a buyer has contracted with a provider and finalized payments on the market (ratio variable). We employed a natural logarithmic transformation for the variable to achieve a less skewed distribution. We denote the transformed variable as $\ln(\text{buyer_exp})$.

Repeat transactions was measured a binary variable to indicate whether a project was a repeat transaction, or first time/one time transaction (*repeat*).

Global labor arbitrage was measured with a continuous variable capturing the PPP-adjusted GDP per capita of the service provider. We denote this variable *ppp*.

Language friction was measured with a binary variable to indicate whether the provider is from an English speaking country (*english*) or not.

ECONOMETRIC SPECIFICATION AND ESTIMATION METHODS

To examine how the two measures of CS and ΔCS affect market performance (continuation, market liquidity, and transaction volume), given that continuation (whether a buyer continues posting RFPs after her first project) is a binary variable, logistic specification with maximum likelihood estimation was chosen (J.M. Wooldridge 2002).

$$(9) \Pr(\text{cont}_{i_2} = 1 | \ln(cs_{i_1}), \text{seeker_type}_{i_1}, \text{project_type}_{i_1}, \text{entrance_time}_{i_1}, \text{controls}_{i_1}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 * \ln(cs_diff_{i_1}) + \beta_2 * \text{seeker_type}_{i_1} + \beta_3 * \text{project_type}_{i_1} + \beta_4 * \text{entrance_time}_{i_1} + \beta_{5-11} * \text{controls}_{i_1} + u_{i_1})}}$$

Market liquidity is a non-negative, discrete variable. Over-dispersion was observed for the distribution of the number of subsequent projects. Thus, a properly specified count model was needed, and a negative binomial model was chosen to estimate the relative effect of CS, CS', and ΔCS on the number of subsequent projects. This is considered a more flexible form for overly dispersed count data.

$$(10) \text{sub_projects}_{i_2} = \beta_0 + \beta_1 * \ln(cs_{i_1}) + \beta_2 * \text{seeker_type}_{i_1} + \beta_3 * \text{project_type}_{i_1} + \beta_4 * \text{entrance_time}_{i_1} + \beta_{4-11} * \text{controls}_{i_1} + u_{i_1}$$

For transaction volume, we used an additional test since subsequent payments was highly correlated with subsequent projects ($r=0.78$). Subsequent payments is a non-negative ratio variable; therefore, we employed ordinary least squares estimation with robust standard error for coefficient estimation.

$$(11) \ln(sub_payments_{it_2}) = \beta_0 + \beta_1 * \ln(cs_{it_1}) + \beta_2 * seeker_type_{it_1} + \beta_3 * project_type_{it_1} + \beta_4 * entrance_time_{it_1} + \beta_{5-11} * controls_{it_1} + u_{it_1}$$

ΔCS was modeled as a function of buyer experience, repeat transactions, labor arbitrage, and language barrier (plus a set of control variables) as covariates. Consistent with the analytical derivation, we used i to index project and t to index time (sequence of projects). Since our data contains information of the same buyer's different projects at different times, there might be correlations among the projects of the same provider because of time-invariant factors. To account for unobserved time invariance of buyers, such as buyer education with panel data, several estimation methods were used. First, a pooled OLS estimation with clustered standard error corrected the standard errors. Second, a fixed effect or a random effect approached was used to account for the unobserved time invariant in the error terms. These estimation models were used to control for unobserved heterogeneity in buyer characteristics when constant over time and correlated with other independent variables. Thus, we specified our antecedent model as follows:

$$(12) \ln(cs_diff_{it}) = \beta_0 + \beta_1 * \ln(outsourcer_exp_{it}) + \beta_2 * \ln(english_{it}) + \beta_3 * (repeat_{it}) + \beta_4 * (ppp_{it}) + \beta_5 * (number_bids_{it}) + \beta_{6-n} * Controls_{it} + \alpha_i + u_{it}$$

We performed resampling for the needs of the analysis of the effects models. We retrieved all the first-time contracts, calculated the continuation, subsequent projects and subsequent payment following those first-time contracts, and matched the data. Overall 38,307 first/one-time projects are obtained for analysis. Maximum likelihood criterion (Logistic analysis) and ordinary least squares with robust standard errors are employed to perform the estimation.

ESTIMATION RESULTS FOR THE EFFECTS MODEL

TABLE 6—LOGISTIC REGRESSION RESULTS (DV=*CONTINUATION*)

Variables	(1)	(2)	(3)
<i>ln(cs)</i>	0.007(0.005)	-	-
<i>ln(cs_adj)</i>	-	0.019***(0.004)	-
<i>ln(cs_diff)</i>	-	-	0.030***(0.005)
<i>seeker_type</i>	1.265***(0.135)	1.261***(0.135)	1.260***(0.135)
<i>project_type</i>	-0.862***(0.081)	-0.864***(0.081)	-0.846***(0.081)
Constant	-0.151(0.154)	-0.180(0.154)	-0.107(0.153)
Wald Chi ² (12)	888.61	903.30	920.85
Pseudo R ²	0.0187	0.019	0.0193

Notes: The total number of observations is 38, 307. We report the robust standard errors in parentheses.
 *** Significant at 0.1 percent level. ** Significant at 1 percent level. * Significant at 5 percent level.

TABLE 7—NEGATIVE BINOMIAL REGRESSION RESULTS (DV=*SUB_PROJECTS*)

VARIABLES	(1)	(2)	(3)
<i>ln(cs)</i>	0.010(0.008)	-	-
<i>ln(cs_adj)</i>	-	0.028***(0.007)	-
<i>ln(cs_diff)</i>	-	-	0.043***(0.007)
<i>seeker_type</i>	1.745***(0.167)	1.740***(0.166)	1.746***(0.164)
<i>project_type</i>	-0.945***(0.095)	-0.943***(0.096)	-0.922***(0.095)
Constant	1.577***(0.213)	1.533***(0.211)	1.646***(0.208)
Lalpha	1.310***(0.015)	1.308***(0.015)	1.307***(0.015)
Wald Chi ² (12)	1040.29	1053.85	1098.72

Notes: The total number of observations is 38, 307. We report the robust standard errors in parentheses.
 *** Significant at 0.1 percent level. ** Significant at 1 percent level. * Significant at 5 percent level.

TABLE 8—REGRESSION RESULTS¹² (DV=*LN(SUB_PAYMENTS)*)

Variables	(1)	(2)	(3)
<i>ln(cs)</i>	-0.001 (0.008)	-	-
<i>ln(cs_adj)</i>	-	0.023*** (0.007)	-
<i>ln(cs_diff)</i>	-	-	0.046*** (0.007)
<i>seeker_type</i>	1.404*** (0.094)	1.400*** (0.094)	1.397*** (0.093)
<i>project_type</i>	-1.029*** (0.077)	-1.032*** (0.077)	-1.003*** (0.077)
Constant	2.751*** (0.144)	2.686*** (0.143)	2.783*** (0.142)
F statistic	145.66	146.68	149.64
R-squared	0.033	0.033	0.034

Notes: The total number of observations is 38, 307. We report the robust standard errors in parentheses.
 *** Significant at 0.1 percent level. ** Significant at 1 percent level. * Significant at 5 percent level.

¹² Control variables were omitted from the main results for brevity. The full regression results are available upon request.

Overall, we find full support for H1. As shown in Table 6, only quality-adjusted CS and Δ CS positively predicted buyer continuity in the market ($\beta > 0$, $p < 0.001$), subsequent projects ($\beta > 0$, $p < 0.001$), and total transaction volume ($\beta > 0$, $p < 0.001$). However, the traditional measure of CS does not predict any of the three market performance outcomes. The results testify to the claim that a quality-adjusted measure of CS is needed and support the notion that the difference of the two measures (Δ CS) is consequential for the marketplace in terms of its performance.

TABLE 9—REGRESSION RESULTS FOR ANTECEDENT MODEL¹³ (DV=LN(CS_DIFF))

Variables	Coefficient Estimates		
	(1)	(2)	(3)
<i>ln(buyer_exp)</i>	0.0305*** (0.00606)	0.0504*** (0.00742)	0.0437*** (0.00831)
<i>lnppp</i>	-0.0835*** (0.00666)	-0.0707*** (0.00620)	-0.0626*** (0.00728)
<i>repeat</i>	0.169*** (0.0142)	0.121*** (0.0126)	0.106*** (0.0131)
<i>same_country</i>	0.0358 (0.0281)	0.0394 (0.0245)	-0.000348 (0.0307)
<i>provider_english</i>	0.199*** (0.0155)	0.187*** (0.0142)	0.198*** (0.0164)
Constant	0.126 (0.0775)	0.0103 (0.0664)	-0.0460 (0.0763)
Observations	159,675	159,675	159,675
F Statistic	67.69	-	57.34
Wald Chi ² (16)	-	1201.13	-
R-squared	0.024	0.018 (within)	0.019 (within)
Estimation	Pooled OLS	RE	FE

Notes: We report cluster-robust standard errors in parentheses. Standard errors are adjusted for 38, 296 clusters in seeker identifier.

*** Significant at 0.1 percent level. ** Significant at 1 percent level. * Significant at 5 percent level.

For the antecedent model, overall the three estimations tried to correct the time invariant unobserved heterogeneity of buyers over time. Even though the estimations yield comparable level of coefficients, for robustness, we tested whether a fixed effects model should be preferred over pooled OLS and a random effects model. We employed the Hausman test (Jerry A. Hausman 1978) to identify whether fixed effects is required to obtain consistent estimates. Since we

¹³ Control variables are omitted from the main results for brevity.

see a difference between the cluster-robust standard errors and the default standard errors of the random effects estimators, we fear that the crucial assumption that α_i and u_{it} being i.i.ds may be invalid. Therefore, we corrected the shortcoming of standard Hausman test by employing the approach suggested by Wooldridge (2002) to construct a robust Hausman test. We thus used a user-written command (M.E. Schaffer and S. Stillman 2006) following Cameron and Trivedi (2009).

Since both Hausman test and the robust Hausman test for fixed effects strongly reject the null hypothesis that random effects estimation provides consistent estimates, we are obliged to interpret the results based on fixed effects estimations. The predictors of *ex-post* additional utility are elaborate below:

First, we tested whether the service buyer's experience is positively associated with ΔCS . The number of completed projects ($\beta=+0.044$, $p<0.001$) positively affected ΔCS . Repeat transactions ($\beta=+0.106$, $p<0.001$) and English as the provider's official language ($\beta=+0.198$, $p<0.001$) both positively affected ΔCS . Provider's PPP-adjusted GDP per capita ($\beta=-0.063$, $p<0.001$) negatively affected ΔCS . This supports our claim that with the same amount of money, on average, providers from poorer countries will work harder than those from richer countries.

D. Robustness Tests

ADDITIONAL ROBUSTNESS CHECKS

We performed several robustness checks to insure the validity of our results. First, scatter plots of observations and dependent variables did not show any pattern for the consequence model, indicating independence of observations (i.i.d.s). The role of multicollinearity was checked with variation inflation factors (VIFs) (Hair Jr et al. 1995), and VIFs were below the suggested threshold ($VIF<3$). We also checked the correlations between variables to amend the low power of

VIF test in large datasets, and no threat to validity was detected. These robustness checks lend further credence to our findings.

ECONOMIC EFFECT SIZES¹⁴

We examined the economic effects (effect sizes) of these predictors because the statistical significance may be an artifact of the sample size. For the effects model, on average, a \$6 (100%) increase in Δ CS will increase the odds of a buyer continuing to post RFPs on the market by 30%. The quality-adjusted measure of CS is two times more predictive than the traditional measure of CS. A \$6 increase in Δ CS will increase 1.4% of total future projects, while a \$6 increase in Δ CS will increase 1.63% of total future payments (\$9.29). In sum, the analysis of the economic effects sizes shows that our predictors are economically important.

For the predictive model, on average, one-time (100%) more projects completed in the market increase Δ CS by 5.2%. And for a given project, if a service provider is from a country with two times the provider's PPP-adjusted GDP per capita, Δ CS will be reduced by 6.3%. If a project is a repeat (versus a first-time project), Δ CS will increase by 10.6%. And if the provider is from a country where English is the official language, Δ CS will be increased by almost 20%.

GENERALIZABILITY OF THE QUALITY-ADJUSTED MEASURE

We do acknowledge that the quality-adjusted measure of CS is most useful in markets for services. Nonetheless, the estimation of CS for commodity products can take advantage of data on pre-purchase and post-purchase feedback ratings for sellers (providers) to derive a disconfirmation function (e.g. similar to our study), to adjust the traditional measure of CS. Accordingly, we expect the proposed quality-adjusted measure to be generalizable to similar and other types of markets.

¹⁴ The economic effects should be interpreted cautiously since there might be non-linear effects.

We also expect the quality-adjusted measure $CS_j' = \bar{V}_j + \frac{(\bar{V}_j - V_j)}{\ln\left(\frac{\bar{q}}{\hat{q}}\right)} \cdot \ln\left(\frac{q'}{\bar{q}}\right) - p_j$ to

generalize to other markets with asymmetric information with feedback systems that require buyers to post their budgets and post feedback for sellers. Therefore, we expect the general form $CS_j' = f(q_j') - p_j$ to generalize to other markets.

V. Discussion

A. Key Findings and Contributions

This study proposed a quality-adjusted measure for CS, which we believe, is particularly salient in markets with asymmetric information. Due to uncertainty (as requirements cannot be perfectly specified ex ante) and asymmetric information (since providers cannot be physically monitored after both parties are contracted), actual ex post quality may deviate from ex ante expected quality, which would impact consumer utility and CS. The study drew upon ECT to revisit the concept of CS and extend existing research on measuring CS. Although the distinction between the traditional measure and quality-adjusted measure of CS (ΔCS) may be intuitive at first brush, it indeed needs to be formalized and empirically tested.

The results testify to the economic role of markets with asymmetric information and the importance of the quality-adjusted measure of CS: First, our results provide empirical evidence for the level of CS in online markets. On average, the buyer reaps an average CS of \$94.4-\$175.5 per project, which is about 69%-128% of the winning bid price (\$137), the amount that the buyer actually paid, which is considerable, implying that buyers are paying much less than what they are willing to pay for the services they outsource in online markets.

Second, we theorized CS in the context of online markets for the outsourcing of services. Given the nature of services, we stress the difference between *ex ante* quality expectation and *ex-post* quality confirmation; nevertheless, we expect our quality-adjusted measure of CS to be generalizable to other markets with asymmetric information (such as eBay.com) since every purchase has a major part of *ex-ante* expectation and *ex-post* evaluation (satisfaction with product/service). As nearly all products and services have a post-purchase evaluation aspect, it is important to take consumer *ex post* satisfaction into account when estimating CS.

Third, our results also stand to confirm the significant difference between the quality-adjusted measure and traditional measure of CS (Δ CS) in terms of their level, effects, and predictors. Though markets with asymmetric information offer great benefits to buyers, given the economic reality of consumer post-purchase satisfaction, we provide evidence that online markets may actually be producing lower surplus when using the quality-adjusted than the traditional CS measure. Our results provide support for the predictive superiority of the quality-adjusted measure. Most important, only the quality-adjusted measure of CS and Δ CS are shown to predict market performance. Finally, buyer's experience, repeat transactions, and the lack of a language barrier are shown to positively affect the *ex-post* extra utility (Δ CS) received by the buyer.

B. Implications for the Predictive Power of the Quality Adjusted CS Measure

The natural question is why *ex post* quality was not factored into CS models? Anecdotal evidence shows many online transactions to end up in dissatisfaction, product returns, and disputes, due to products not matching the buyers' needs, product defects, and low quality service (such as fulfillment delays) (WSJ 2008); thus, total product returns are very high (Dave Blanchard 2005, 2007). Therefore, when buyer *ex-post* satisfaction is taken into account, previous research

employing the traditional CS measure may have overestimated the true CS level. By leveraging ECT to integrate the notions of *ex-post* quality and satisfaction to CS theories, we conceptually show that the traditional measure of CS may either inflate or underestimate the level of CS because it is only an *ex-ante* concept. Prior studies may have either over-estimated or under-estimated CS because the implicit assumption was that buyers are fully satisfied with the products they receive, albeit the reality is that buyer's satisfaction is dependent on the confirmation / disconfirmation of their expectations of product/service quality. Empirically, the traditional measure of CS is shown to inflate the true CS and not predict market performance. Despite our focus on online markets for outsourcing of services, our quality-adjusted CS measure could apply to virtually all products. Thus, it is important to include consumption experience and ex post satisfaction when calculating CS to avoid a biased estimation of societal welfare.

Since the function and sustainability of markets with asymmetric information depend to a large extent on "job supply", it is important for these markets to increase CS with superior designs. First, since experienced buyers enjoy higher CS, the intermediary should educate new buyers how to navigate the marketplace so they do not suffer from low surplus that may cause them to exit the market. Second, since global labor arbitrage seems to further increase CS for buyers, markets can facilitate service projects between richer and poorer countries. Third, since the language barrier is shown to reduce CS, it is important for signals about the provider's language proficiency (English or other languages) to be visible.

C. Limitations and Future Research

This paper makes several assumptions that may limit its generalizability. First, in the empirical part, as far as the budget as a proxy for *ex-ante* WTP is concerned, it is possible that the buyer would strategically enter an amount to attract the

optimal number of providers to bid for services. Future research could examine whether and how different types (such as experienced or inexperienced buyers) would strategically design their RFPs to maximize their CS.

Second, we also observed that variance of CS with quality-adjusted measure is larger than the traditional CS measure. This could imply that buyer risk (uncertainty) has not been fully compensated. Therefore, future research can leverage uncertainty theories to further argue that buyers in service e-markets may extract a lower surplus than they expected on the market level.

VI. Concluding Remark

This study makes an initiative in better understanding how and by how much surplus is accrued in markets with asymmetric information where *ex ante* expectations are susceptible to deviation from the actual *ex-post* quality received. Our work contributes to the literature by quantifying the economic benefits of markets with asymmetric information. The growing value for buyers is the main reasons that these markets can survive and thrive despite information asymmetry. Our study calls for a more precise measure of CS that reflects economic reality. The quality-adjusted measure helps make more accurate predictions in terms of the level, effects, and predictors of CS in markets with asymmetric information.

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