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Content Contributor Management and Network Effects in a UGC Environment

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The success of any user-generated content website depends crucially on its asset of content contributors. How firms should invest in the acquisition and retention of content contributors represents a novel question that is particularly important for these websites. We develop a vector autoregressive (VAR) model to measure the financial values of the retention and acquisition of both contributors and content consumers. In our empirical application to a customer-to-customer marketplace, we find that contributor (seller) acquisition has the largest financial value because of their strong network effects on content consumers (buyers) and other contributors. However, the wear-in of contributors' financial values takes longer because the network effects need time to be fully realized. Our simulation-based studies (i) shed light on the value implications of "enhancing network effects" and (ii) quantify the revenue contributions of marketing newsletter campaigns. Our results indicate that enhancing network effects in complementary ways can further increase the marginal benefits of acquisition and retention. We also find that simply tracking click-throughs may vastly underestimate the values of marketing newsletters—in our case, by more than a factor of 5—which may lead to suboptimal marketing effort allocation.

Key words: UGC; content contributors; VAR; lifetime value; acquisition; retention; C2C marketplace; network effects
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1. Introduction

User-generated content (UGC) represents one of the most dynamic media forms on the Internet. Video-sharing websites such as YouTube, online encyclopedias such as Wikipedia, and customer-to-customer (C2C) marketplaces such as eBay are rapidly taking over many of their traditional counterparts.[1] The achievements of UGC websites often stand in stark contrast with their sizes. In 1998, the two-year-old eBay made revenues of USD 4.7 million with merely 30 employees. Similarly, back in 2006, YouTube was able to serve more than 100 million videos daily with 67 employees. The impressive growth of the UGC sector is a testimony to the power and impact of *content contributors*. In 2008, more than 82 million people in the United States created online content.[2] It is estimated that content contributors add approximately 20 hours of video materials every minute on YouTube. Interestingly, a pure C2C website such as the early eBay, unlike a traditional business-to-consumer (B2C) website such as Amazon, cannot directly decide on its content (e.g., product assortment, inventory, retail display, or even pricing). These factors can only be improved through careful acquisition and management of both sellers and buyers. Said differently, the financial success of any UGC website depends critically on its ability to actively manage and grow content contributors in addition to content consumers. Inability to do so was one of the reasons why firms such as Chemdex.com could not reach the point where they could turn a profit.

In this paper, we take a first step in helping firms assess the value of content contributors and content

[1] UGC is a relatively new phenomenon, and no "formal" definition has been given in the literature. People may have different opinions on whether C2C websites such as eBay can be classified as UGC applications. In this paper, we use the term "UGC website" as a rather general term referring to websites that do not provide their key "products" by themselves. In our empirical application, we study a C2C website where all products are listed by users of the website. Although the framework of analysis we propose can be applied to other UGC contexts, we cannot claim the generalizability of our empirical results.

[2] See Verna (2009).

consumers. In the process, we highlight the importance of understanding the network dynamics that underpin these economic values. Our results provide guidance on the marketing actions that can be undertaken by the firm to acquire and retain their contributors and consumers. Empirically, we apply the proposed analysis to a large UGC-type website, namely, a C2C marketplace. Our framework of analysis can be similarly applied to other UGC settings.

Theoretically, a UGC website can be seen as a two-sided marketplace, with content contributors and content consumers as the two sides of the market, and the website as the platform where the two groups of users interact. The value of contributors is manifested through their network effects on both content consumers and other content contributors. The network effects can be either direct (where the different groups of users derive value from interactions) or indirect (where users benefit from a larger variety of content). Similarly, the presence of more content consumers also benefits the contributors. Thus the *acquisition* of content contributors may lead both to more content consumers joining the website and to increased activity of existing consumers and contributors, which, in turn, translate into financial returns for the website. The *retention* of existing contributors or consumers will bring value to the website in a similar manner.

Measuring the value of customers has been of long-standing interest in the customer lifetime value (CLV) literature. Most traditional models in the CLV literature are based on individual-level cash flow analysis (Fader et al. 2005, Gupta et al. 2006, Venkatesan and Kumar 2004). Cash flow analysis quantifies both the present value of a customer and how this value unfolds over time. Unfortunately, traditional CLV models eminently suited for one-sided markets are inadequate for UGC settings because they do not accommodate the strong network effects among content contributors and content consumers, which are idiosyncratic to UGC settings. To address this challenge, a number of recent studies have introduced *persistence modeling* (Dekimpe and Hanssens 2004) techniques, notably the vector autoregressive model (VAR), for the measurement of CLV (see Gupta et al. 2006 for a review).

This paper adds to the above-mentioned literature and applies the VAR model to measure the average value of both contributors and consumers in a UGC setting. We quantify the values of both acquisition and retention of contributors and consumers and the magnitudes of network effects, and we detail their evolution over time. Based on these empirical estimates, we perform VAR-based simulations to answer two key managerial questions. (1) Given the importance of network effects, how can a UGC firm measure the marginal return from specific marketing actions so as to inform its marketing mix optimization? In our empirical context, we study how the firm can measure the cumulative revenue contribution of e-mail newsletters, beyond just tracking the clicks they get. (2) When the firm wants to enhance network effects, which directions should it focus on? For example, should the firm emphasize promoting the interactions between the consumers or provide guidance to contributors so that they generate content that is more relevant for the consumers?

We use aggregate-level data from a C2C website where sellers serve as the primary content contributors by designing their virtual shops and showcasing the products, and buyers browse and purchase the products. This setting illustrates the methodology and a set of simulation analyses, which can be applied by any company interested in answering questions about contributor management in UGC settings. Although the VAR model is not the only model to answer the questions above, it is well suited to our specific empirical setting and gives results that are consistent among themselves.

The key results from our analysis for this particular UGC website are summarized as follows.

(1) On a per-unit basis, seller acquisition has the largest cumulative financial value as well as network effects, followed by buyer acquisition, seller retention, and finally buyer retention. These results, which may seem in contrast to conventional wisdom that often retention is preferred to acquisition (e.g., Reichheld and Sasser 1990, Sheth and Parvatiyar 1995, Reinartz and Kumar 2000), are a consequence of the significant network effects that characterize two-sided markets. In fact, network effects constitute more than 80% of the total revenue contributions of new sellers and buyers who bring more than four to five times the revenue than returning sellers and buyers, respectively.

(2) Although new sellers and buyers are financially more valuable, it takes longer for their values to unfold, as a consequence of network dynamics. As a result, acquiring new sellers and buyers is even more valuable relative to retaining existing sellers and buyers when the firm has a longer planning horizon.

(3) The long-term financial returns from marketing activities such as e-mail newsletters are considerably greater than their short-term returns. This is again a consequence of the network effects that they help unleash among the sellers and buyers. For the firm we study, every thousand e-mail newsletters increase revenue by 6 to 10 euros over the long term, whereas their short-term marginal contribution is 1 to 2 euros. Thus, simply tracing click-throughs may underestimate the values of marketing newsletters by more than a factor of 5 and lead to suboptimal marketing effort decisions.

(4) Enhancements of the network effects in different directions are complementary decisions in the economics sense (Topkis 1998). The marginal return from each system increases when other systems are implemented or improved. In our empirical context, net of cost, enhancing the network effects of new sellers on other new sellers, represents the most profitable direction.

The rest of this paper is organized as follows. In §2, we review the related literature. In §3, we describe our empirical setting, the model setup, specification tests, estimation and identification issues, and model fit results. In §4, we present our main findings based on impulse response functions (IRFs). In §5, we present the simulation results to answer the aforementioned managerial questions. In §6, we study the robustness of our results over time as well as across product categories. Finally, in §7, we conclude and discuss possible future research directions. We present some additional analyses, including a forecast error variance decomposition and a heuristic that decomposes the total values of customers into direct and network components in the electronic companion. An electronic companion to this paper is available as part of the online version that can be found at http://mktsci.journal.informs.org/.

2. Literature Review

Our paper is related to several streams of literature. First, it is within the context of the emerging literature on UGC, social networks, and social commerce. Various studies have empirically examined the impact of online social media on firms. For example, the literature has examined the relationship between social network structure and the diffusion of products (Goldenberg et al. 2009), the properties and impact of word of mouth (Trusov et al. 2009, Villanueva et al. 2008, Chevalier and Mayzlin 2006), user behavior (Mathwick et al. 2007) and the implications for firm decisions, such as brand building (Muñiz and Schau 2005), and the impact of network formation on social commerce (Stephen and Toubia 2010). Our paper examines an issue not discussed in this stream: the overarching consumer *and* contributor asset management problem.

Second, it is related to the marketing and economics literature on two-sided markets. Two-sided markets have been formally modeled in the theoretical industrial organization literature (Armstrong 2006, Rochet and Tirole 2006). One qualitatively robust finding is that when network effects are sufficiently strong, the firm may find it beneficial to subsidize one group of users to foster growth (Fath and Sarvary 2003). In the empirical literature, cross-group network effects have been found in various contexts (Nair et al. 2004, Yao and Mela 2008, Tucker and Zhang 2010). Our work not only measures the magnitudes of network effects in a UGC setting but, more importantly, links network effects to the measurement of the financial values of contributors and consumers. In addition, we explore the managerial implications of enhancing network effects using simulations with empirical estimates from real data.

Third, our study is related to the marketing literature on CLV and customer equity management (Villanueva and Hanssens 2007). Marketing researchers have shown that customers are among the most important assets of a firm, and we now have advanced methodologies for computing the value of this asset (see Gupta et al. 2006 for a review of the various modeling approaches). Whereas the traditional approaches are usually based on individual-level models (Fader et al. 2005, Gupta et al. 2006, Venkatesan and Kumar 2004), a number of recent studies have developed aggregate-level models using VAR models (Villanueva et al. 2008) and alternative methodologies (Gupta et al. 2009, Hogan et al. 2003). Our study is closely related to Villanueva et al. (2008) both conceptually and methodologically. Whereas Villanueva et al. (2008) measure the value of customers acquired from different channels, we consider the two-sidedness of the market and study both consumers and contributors. In addition, we study both acquisition and retention. Our paper is also conceptually close to Gupta et al. (2009), which derives measures of customer value based on a diffusion model. Unlike that work, which considers only acquisition, we focus on both acquisition and retention and study the relative impact of network effects on the values of these two. Moreover, because we use a different methodology, a VAR model versus a diffusion model, we can study how all effects unfold over time and suggest, among others things, different managerial actions depending on the time horizon of a firm. The diffusion model by Gupta et al. (2009) and our VAR model both suggest the existence of significant network effects, among other things.

Finally, our work methodologically relates to the literature that uses persistence modeling techniques such as VAR (Dekimpe and Hanssens 1995, Pauwels 2004, Luo 2009, Trusov et al. 2009, Stephen and Toubia 2010). We follow the standard VAR framework outlined by Dekimpe and Hanssens (2004).

3. Data and Methodology

3.1. Data

We obtain weekly data from a major C2C website in Europe. The website has been operational since 2001 and is currently the leading website of its kind in several European countries, with millions of users.

The traded product categories range from books and DVDs to electronics, home appliances, and furniture. On average, about 80,000 transactions take place each week, and the total transaction value across all products are several million euros per week. The website is run completely on a C2C basis. In other words, the company itself does not list any product. Sellers come to the website, design their virtual shops, decide the assortment, describe it with detailed product descriptions, and set prices. Buyers can browse, purchase, and write product and seller reviews. Overall, the website resembles eBay with the exception that the goods are sold via a set price format instead of auctions. Based on discussions with the company's managers, we designate sellers as the primary group of content contributors on the website.

Our data include the number of new sellers, returning sellers, new buyers, returning buyers, and the total commission earned by the website per week. The observation period lasts from mid-2005 to mid-2009, consisting of a total of 201 weeks. Table 1 summarizes some descriptive statistics. The variables are as follows:

Number of new sellers: The number of new sellers who have sold a product for the first time in a given week.

Number of returning sellers: The number of returning sellers who have sold at least one product in a given week but also in previous weeks.

Number of new buyers: The number of registered buyers who have purchased a product for the first time in a given week.

Number of returning buyers: The number of returning buyers who have purchased products in previous weeks and have purchased at least one product in the given week.

Total weekly commission: The total commission earned by the website in a given week. The total commission is a constant fraction of the revenue generated from buyer–seller transactions.

The time evolutions of the key variables are illustrated in Appendix A.6 of the electronic companion. We use the logged values for all the time series in the model. We denote these variables as LOS_t (log value of the number of returning sellers at time t), LNS_t (log value of the number of new sellers at time t), LOB_t (log value of the number of returning buyers at time t), LNB_t (log value of the number of new buyers at time t), and LC_t (log value of commission at time t).

Table 1 **Descriptive Statistics of the Data**

Variable	Mean	Std. dev.	Min	Max
Number of new sellers	1,589	374	852	2,657
Number of returning sellers	22,637	5,917	12,875	36,235
Number of new buyers	11,401	2,747	6,548	21,198
Number of returning buyers	32,068	8,800	17,444	57,250
Total weekly commission (euros)	269,449	70,095	150,057	508,973

Note. Numbers represent weekly aggregates.

A number of caveats apply to our data. First, as in most UGC applications, the boundary between content contributors and content consumers is not clear-cut. For example, in YouTube, even those users who never make a video contribute to the website by leaving comments, tagging videos, and giving ratings. Similarly, in our C2C marketplace, buyers also contribute by writing product reviews. Second, like many website-based studies, we can only count sellers and buyers by registrations on the website, without knowing whether the same person in the real world registered under different IDs. For example, the same person may both buy and sell on the website under different buyer and seller IDs or even possess multiple buyer and seller IDs. This affects the interpretation of our results in §4. Third, by using aggregate-level data, all our empirical results are limited to the average values on the entire seller/buyer population. That said, we investigate the heterogeneity in seller/buyer values in §6.

3.2. Model Selection and Estimation

We adopted a VAR model to capture the interdependent evolution of the variables of interest. The evolution of each variable (the numbers of buyers and sellers as well as total commission) are explained by the lag of itself and other variables. By treating each variable as potentially endogenous, the VAR model is particularly suitable to capture the dynamic and complex interdependence between the variables of interest without making stringent identification assumptions. Based on the estimated VAR parameters, simulation techniques can be applied to derive the long-term impact of a shock in one variable on all the other variables.

Our analysis follows the standard procedure of VAR modeling, which consists of the following steps: (1) unit root tests to determine the stationarity of the variables; (2) cointegration test when the variables are nonstationary; (3) deciding model specification (VAR in levels, VAR in differences, or error correction (VEC) forms) based on unit root and cointegration tests results; and (4) deciding model specification (number of lags and exogenous variables) based on information criteria. These procedures are discussed in detail in Dekimpe and Hanssens (2004). Our final step (5) is imposing identification restrictions and deriving IRFs.

We first performed the augmented Dickey-Fuller (ADF) unit root test to test the null hypothesis of a unit root and the KPSS test (Kwiatkowski et al. 1992) to test the null hypothesis of stationarity. The ADF test statistics range from −4.240 to −3.751, all below the 5% critical value of −3.437. Therefore we rejected the null hypothesis of unit root at the 5% confidence level. The KPSS test statistics ranged from 0.078 to 0.114, all below the 5% critical value of 0.146. Hence we could not reject the null hypothesis of stationarity. We applied the iterative procedure recommended by Enders (2004) to decide whether a time trend should be included in the test. The procedure suggests that a time trend should be included in the ADF tests.

Taken together, the tests agree with each other and suggest that all the variables are trend stationary. Based on the above results, we estimated the following standard-form VAR model in levels (Dekimpe and Hanssens 2004):

$$\begin{bmatrix} LOS_t \\ LNS_t \\ LOB_t \\ LNB_t \\ LC_t \end{bmatrix} = \bar{\alpha} + \bar{\vartheta} t + \sum_{j=1}^{J} B_j \begin{bmatrix} LOS_{t-j} \\ LNS_{t-j} \\ LOB_{t-j} \\ LNB_{t-j} \\ LC_{t-j} \end{bmatrix} + \sum_{k=1}^{4} \bar{\nu} S_{kt} + \sum_{q=2005}^{2009} \bar{\lambda} C_{qt} + \bar{\varepsilon}_t. \qquad (1)$$

We include the following exogenous variables in the system: a linear time trend (t), seasonal dummies (S_{kt}), and dummies for Christmas shopping seasons (C_{qt}). Each B_j is a 5×5 matrix. For notational convenience, we index the variables as $1 =$ returning sellers, $2 =$ new sellers, $3 =$ returning buyers, $4 =$ new buyers, and $5 =$ commission. In the standard-form VAR model, because the right-hand side only contains lagged endogenous variables, ordinary least squares yields consistent estimates. In Appendix A.1 of the electronic companion, we explain the underlying structural-form VAR model, which includes theoretically meaningful parameters.

We used Schwarz's Bayesian Information Criterion (SBIC) (as in Dekimpe and Hanssens 1995 and Villanueva et al. 2008) to select the model parameters. Based on SBIC, the optimal lag length is set to 1. The linear time trend captures the (unobserved) natural growth of the Internet market over time, a typically needed control for spurious correlations (see Villanueva et al. 2008 and Trusov et al. 2009 for similar arguments). We allowed a quadratic term of time trend in the system, which was later excluded because it decreased SBIC. We finally performed the Portmanteau test (Lütkepohl 2005) to test for residual autocorrelation and could not reject the null hypothesis of white noise.

We identified the contemporaneous effects from a Cholesky decomposition of the variance–covariance matrix of the residuals. This follows the widely used identification assumptions, sometimes called contemporaneous ordering (Villanueva et al. 2008) or orthogonalizing transformation (Luo 2009). Based on discussions with the firm, in the basic model, we impose the following ordering of the variables: LOS_t, LNS_t, LOB_t, LNB_t, and LC_t.[3]

4. Empirical Findings

We report our VAR parameter estimates and R^2 of each equation in Appendix A.5 of the electronic companion. As is typically done in the literature, we do not interpret the individual parameters themselves but focus on the IRFs (see Dekimpe and Hanssens 2004 for this argument and a formal definition of the IRF). The IRFs trace the change in the response variable over time when there is an unexpected shock[4] to the impulse variable. The cumulative IRF (CIRF) measures the total impact of the unexpected shock in the impulse variable on the response variable. We are interested in the following IRFs:

(1) When the *number of new buyers/sellers* is the impulse variable, and the *total commission* is the response variable, the CIRF measures the *revenue contribution* of an unexpected addition of a new buyer/seller. We call this the revenue contribution of *one instance of acquisition.*

(2) When the *number of returning buyers/sellers* is the impulse variable, and the *total commission* is the response variable, the CIRF measures the *revenue contribution* of an unexpected "reactivation" of an existing buyer/seller. The "unexpected reactivation" of a returning buyer/seller means that because of a shock that is not predicted by the explanatory variable, an otherwise inactive existing buyer/seller becomes active in buying/selling products—which is what we call *one instance of retention*.

(3) When *the number of new buyers/sellers* is the impulse variable, and *the number of new buyers/sellers* is the response variable, the CIRF measures the *additional users joining the website* over time when there is an unexpected addition of a new user. It is a cumulative measure of new users' *network effects* on other new users.

[3] As a robustness check, we also used an alternative ordering, LOS_t, LOB_t, LNS_t, LNB_t, and LC_t, which led to similar results. We believe these two orderings are the only reasonable choices for the following reasons. First, it is reasonable to assume that the existing users should have contemporaneous effects on the new users, but not vice versa. Second, the buyers can observe the number of product postings—which strongly correlates with the number of actual sellers—immediately, but the sellers cannot observe the number of active buyers in the same time period. Therefore the number of sellers has contemporaneous effects on the number of buyers, but not vice versa. Finally, the numbers of both new and returning buyers sellers should have contemporaneous effects on the commission, but not vice versa.

[4] We use the term "unexpected" in its standard sense in the VAR literature. It means the shock is unpredicted by the exogenous variables, such as time trend and seasonal dummies.

(4) When *the number of returning buyers/sellers* is the impulse variable and *the number of new buyers/sellers* is the response variable, the CIRF measures a type of *network effects* created by the reactivation of an existing user.

(5) When *the number of new buyers/sellers* is the impulse variable, and *the number of returning buyers/sellers* is the response variable, the conceptual meaning of the CIRF is ambiguous. Following the acquisition of one user at time 0, we may observe more returning users in the subsequent periods. However, we cannot discern whether a returning buyer/seller is the lately acquired buyer/seller herself or an existing buyer/seller who had already joined the website before the acquisition. For this reason, we only focus on new users when we discuss the results about network effects in §§4 and 5.2. The network effects of new users on existing users are important, but we cannot measure them.

Because CIRFs are functions of time, they provide measures about the short-term as well as the long-term cumulative effects. For ease of exposition, we transform the CIRF values from percentage terms (derived from the log formulation) back into euro terms. The transformation is $\Delta Y/\Delta X = (\bar{Y}/\bar{X}) \cdot (\Delta \ln Y/\sigma_{\ln X})^5$ and is standard in the literature (e.g., Trusov et al. 2009). This allows us to report the financial and network values of one additional new or returning buyer/seller. A similar analysis can be done using percentage terms (e.g., the impact of an unexpected 1% increase of the number of new or returning buyers/sellers). We focus on the actual numbers of customers because they are managerially more relevant.

4.1. Values of Acquisition vs. Retention and of Sellers vs. Buyers

Our first set of results answers the following question: How much cumulative value (direct cash flow and the indirect network value) does one instance of acquisition or retention of a seller or buyer generate?

Table 2 presents the cumulative long-term revenue contributions of buyer/seller acquisition or retention. The firm under study provided range estimates of the marginal acquisition or retention costs. These costs are as follows: 12–60 euros for seller acquisition, 5–25 euros for buyer acquisition, 0–10 euros for seller retention, and 0–5 euros for buyer retention.[6] Together with these cost estimates, the results show that acquisition of sellers or buyers is more valuable than retention of the same type of users by more than a factor of 4 or 5 in this case. This result at first glance seems in marked contrast with findings in the CLV literature (e.g., Reichheld and Sasser 1990, Sheth and Parvatiyar 1995, Reinartz and Kumar 2000) wherein often retention is preferred to acquisition even when the costs are comparable. The logic for those results is based on two-sided learning (i.e., returning customers tend to become more loyal, less price sensitive, and easier to serve over time). Our results reveal that once *network effects* are taken into account, acquisition becomes more valuable because newly acquired users (i.e., content contributors and consumers) generate network effects that have financial returns to the firm significantly beyond the cash flows they generate individually. It should be noted that the cumulative values of acquisition versus retention are firm- and data set-dependent, and our results may not generalize to other data sets. However, the essential point is that CLV measures for a business going forward need to consider both the direct financial returns from an individual buyer/seller as well as the additional financial contributions they generate through their network effects on other buyers and sellers.

Table 2 Cumulative Revenue Contributions of Buyers and Sellers

	Cumulative revenue contribution
One new seller	242*
One new buyer	94*
One returning seller ("one instance of retention")	45*
One returning buyer ("one instance of retention")	11

Notes. These numbers are robust to the change of variable ordering. The alternative ordering of variables LOS_t, LOB_t, LNS_t, LNB_t, and LC_t leads to the following estimates (in the same order as in the table): 228, 92, 43, and 15.

$^*p < 0.05$.

We next compare the cumulative values of one buyer versus one seller.[7] We find that seller acquisition is more valuable than buyer acquisition on a per-unit basis, and one instance of seller retention is more valuable than one instance of buyer retention. These results suggest the necessity of developing innovative marketing campaigns targeted at acquiring and retaining

[5] $\Delta \ln Y$ stands for the IRF derived from the log formulation, where the shock is of one standard deviation size. This number is normalized by the standard deviation of the $\ln X$ sequence to obtain the X arc elasticity of Y. Finally, we divide the quantity by the mean levels of impulse variable (X) and multiply it by the mean level of the response variable (Y) to translate the elasticity back into marginal effect.

[6] The acquisition cost is partly estimated based on the advertising price on Google AdWords and the estimated conversion rate. The estimation of retention is trickier because retention involves substantial fixed cost investment (designing an e-mail newsletter campaign and product recommendation system, etc.), but the marginal cost is low.

[7] As discussed in §3.2, we cannot observe directly whether it is the same individual behind different buyer and seller IDs. An individual in the real world may both buy and sell online under multiple different IDs. According to the firm's best estimates, approximately 50% of sellers are also buyers on the website, and 10% of the buyers also sell.

sellers—an issue that was previously ignored and is currently being actively explored by the company.

We perform significance tests based on Monte Carlo simulation (Lütkepohl 2005) with 250 simulations and find that the revenue contribution differences are significant. The test details and results are presented in Appendix A.8 of the electronic companion. In Appendix A.7 of the electronic companion, we plot the IRFs with 95% confidence intervals.

Overall, the revenue contribution estimates seem strikingly large compared with the acquisition and retention costs provided by the company. For example, the cost of acquiring one new seller is estimated to be 12–60 euros, whereas the revenue contribution of one seller is about 242 euros. This suggests underinvestment by the firm on both acquisition and retention. Interestingly, the cost ranges are on the same order of magnitude as the individual revenue contributions (net of network effects), which we derive in Appendix A.3 of the electronic companion as well as the traditional CLV estimates provided by the firm. This suggests that the firm is possibly trying to optimize its acquisition and retention efforts based on the cash flow measures of lifetime values, but the underappreciation of network effects leads to severe underinvestment.

Finally, we note that these results should not be interpreted as downplaying the importance of buyers/consumers relative to sellers/contributors. Although the individual revenue contribution of each buyer is small, the overall contribution of buyers is significant as they are a much bigger segment in size relative to the sellers. For example, when the number of new buyers is increased by 1% in a certain week, the total commission cumulatively increases by 4% (of the weekly amount). When the number of new sellers is increased by 1%, the commission only increases by 1.3% cumulatively.

4.2. Network Effects

We now consider the following question: How large are the network effects? For example, what is the impact of new sellers on new buyers, and vice versa?

We measure the network effects as the number of additional users joining the website following one instance of acquisition or retention using CIRFs, as defined above. "Network effect" is a general term referring to a complex set of more specific effects. For example, observational learning (Tucker and Zhang 2010) takes place when the act of some sellers joining the website leads to inference of the profitability of selling in this website, thereby inducing other sellers to join the site as well. New sellers joining the website also enrich the product offering and lead to greater availability of the popular products. Similarly, buyers have network effects on other buyers and sellers through their product reviews and word of mouth (Chevalier and Mayzlin 2006). Our measure of network effects captures the accumulation of all these effects.

Table 3 **Network Effects**

	Additional new sellers	Additional new buyers
One new seller	2.8[*,a]	10.8[*]
One new buyer	0.7[*]	5.6[*]
One returning seller ("one instance of retention")	0.2[*]	2.3[*]
One returning buyer ("one instance of retention")	0.04	−0.8

[a]The CIRF is 3.8 when the number of new sellers is both the impulse and response variable. Thus the additional number of new sellers (excluding the unexpected initial acquisition) equals $3.8 - 1 = 2.8$.
[*]$p < 0.05$.

Table 3 summarizes our results. The network effects reported here correspond to the converged cumulative effects, taken as the CIRF at the 16th week. For example, the network effects of new sellers on additional new buyers correspond to 10.8. This means that following the unexpected acquisition of one new seller, the number of new buyers joining the website will be 10.8 more compared with the scenario where the unexpected seller acquisition does not take place.

Table 3 indicates that the acquisition of new sellers has the largest network effect, which underpins the large financial value of seller acquisition highlighted earlier. Acquisition of new buyers has the second-largest network effect. Retentions of sellers and buyers have smaller network effects. Discussion with the company reveals that the large differences in network effects between new and returning sellers/buyers may be explained by a seller's or buyer's propensity to engage in so-called "nontransaction activities." For example, during the first weeks after joining the website, sellers spend considerable effort in designing their virtual shops, and similarly, buyers are more likely to write product reviews. Although these activities do not generate transactions directly, they significantly increase the network benefits a new seller/buyer generates. On the other hand, returning sellers engage relatively less on these nontransaction activities.

These findings reveal that, in agreement with Table 2, the most valuable events (seller and buyer acquisition) also have the largest network effects. This suggests that network effects are the key driver behind the large values of seller and buyer acquisition. The magnitudes of network effects indicate that in our C2C marketplace, the valuation of sellers and buyers cannot be done through a simple cash flow analysis, where the impact of one seller or buyer on other sellers and buyers is ignored.[8] In fact, given

[8] This observation is in accordance with the conclusions of Gupta et al. (2009).

that one new seller will bring in a total of 3.8 sellers, the cash flow generated by one seller is approximately 25% of her total revenue contribution. Similarly, the cash flow generated by one new buyer is less than approximately one-sixth of her total revenue contribution. We further develop this reasoning in Appendix A.3 of the electronic companion to decompose the values of buyers and sellers into a direct component and a network effects component.

The network effects of a new seller/buyer on existing users cannot be precisely quantified for the reasons explained in the beginning of §4. However, our results do indicate the existence of such effects. Our IRFs show that when there is an unexpected unit shock to the number of new sellers at time 0, the number of returning sellers at time 1 increases by 1.7, at least 0.7 of whom must have joined the market before the acquisition takes place. By time 1, the number of returning buyers has increased by 3, at least 2.6 of whom must have already been in the marketplace before the seller acquisition because the acquisition only leads to about 0.4 additional new buyers at time 0. Therefore, existing sellers and buyers are indeed more likely to return to the website because of the acquisition of a new seller.

Traditionally, acquisition and retention are often posed as distinct managerial decisions between which the firm has to allocate its resources. With network effects, the acquisition and retention decisions become, as expected, more interdependent. In some circumstances, acquisition of new users can be a way to retain existing users. We further develop this argument in Appendix A.4 of the electronic companion.

4.3. Accumulation of Values Over Time

We now move to the following question: How do the financial values and network effects realize over time?

Table 2 showed the long-run cumulative revenue contributions of seller/buyer acquisition or retention. We also obtain their short-term contributions by examining the IRF in the first week. The short-run revenue contributions are 29 euros for one new seller, 14 euros for one new buyer, 28 euros for one returning seller, and 9 euros for one returning buyer. These indicate that the difference in revenue contribution between retention and acquisition is much smaller in the short run. For example, in the first week, retaining an existing seller generates about the same amount of revenues as one new seller (28 versus 29 euros). In the long run (cumulatively), however, acquiring one seller brings in five times more revenue than retaining one seller.

To shed more light on how the values accumulate over time, we calculate the number of weeks it takes for the cumulative revenue contributions and network effects to wear-in. It takes 11 weeks for a newly acquired seller to realize 95% of her cumulative revenue contribution and 6 weeks for a retained seller to realize 95% of her cumulative revenue contribution. The wear-in periods for both revenue contributions and network effects are shown in Table 4.

The results indicate that although buyer and seller acquisitions are more valuable in the long run, it takes longer for these impacts to be realized. What underlies the long wear-in periods of the value of seller and buyer acquisition? Network effects serve as one explanation. The values of new sellers and buyers are composed of direct effects and even larger indirect network effects. For example, acquiring a new seller may bring in more sellers by word of mouth, and these sellers, in turn, attract more buyers by enriching the product variety of the website as a whole. These indirect effects may be large in magnitude, but they also take time to realize, as buyers and sellers need time to observe and react to the growth of the website.

Logically, the complete wear-in of the *network effects* of a user must *precede* the complete wear-in of her *value.* For example, it takes 8–12 weeks for the network effects of new users to reach 95% of their cumulative level, and it takes approximately the same length of time for the revenue contributions of new buyers and sellers to wear-in. The long wear-in periods for network effects indicate that network effects indeed serve as explanations for the long wear-in periods for the revenue contributions of buyer/seller acquisition. Taken together, the results in Tables 2–4 establish a consistent positive relationship between the values, network effects, and lengths of wear-in periods for buyers and sellers. In short,

(1) There is a relation between a user's revenue contributions, network effects, and wear-in periods. Seller/buyer acquisitions have large values and large

Table 4 **Wear-In Periods of Revenue Contributions and Network Effects**

	Revenue contributions reach 95% of their cumulative levels	Network effects reach 95% of their cumulative levels (new sellers, new buyers)
One new seller	11	(8, 11)
One new buyer	12	(11, 12)
One returning seller ("one instance of retention")	6	(6, 5)
One returning buyer[a] ("one instance of retention")	1	(1, 1)

Note. The wear-in periods of network effects are shown in pairs: the first number stands for the wear-in period of the network effect on new sellers; the second number stands for the effects on new buyers.

[a]Recall that the cumulative revenue contribution of one returning buyer at week 16 (see Table 2) is not significantly different from zero. We report the time period it takes for the value to reach 95% of the maximal cumulative value, which is significant.

network effects, but it takes longer for their values to fully realize.

(2) The wear-in of network effects precedes the wear-in of revenue contributions.

In Appendix A.2 of the electronic companion, we also explore these insights using the forecast error variance decomposition (Enders 2004) technique. In Appendix A.4 of the electronic companion, we show that the differential wear-in periods of retention and acquisition have implications for the firm's resource allocation decisions under different planning horizons. For example, a firm with a longer planning horizon should shift more resources to seller acquisition from seller retention compared with the case of a company with a shorter planning horizon.

5. Managerial Implications

We use VAR-based simulations to highlight the implications for two sets of managerial actions: (1) sending marketing newsletters and (2) network effect enhancement. Optimizing the level of marketing mixes (in this case, sending marketing newsletters) is an essential issue for any type of company, and C2C marketplaces or UGC firms are no exceptions. Enhancing network effects is a novel but central decision for C2C marketplaces and UGC-based companies. Specifically, we consider the following.

(1) Sending marketing newsletters: When the firm wants to optimize the number of marketing newsletters sent each week, how should it quantify the marginal benefit of sending more newsletters? We compare the value of newsletters estimated with two different approaches.

(2) Enhancing network effects: Given the importance of network effects, what is the marginal benefit of enhancing network effects? When the firm wants to enhance network effects, which directions should it focus on? For example, should the firm focus on promoting the interactions between the buyers or on implementing word-of-mouth referral programs among the sellers?

5.1. Sending Marketing Newsletters

The results thus far have quantified the financial values of new and returning users. We now examine the impact of the firm's marketing actions on the size of the buyer/seller networks and the firm's commission. Optimizing the promotional activities is a problem of great managerial interest to the firm, and we focus in this section on marketing newsletters, which the firm considers as their primary marketing tool. We develop a simulation methodology to calculate the marginal increase in revenue when 1,000 marketing newsletters are sent. The marginal revenue increase can be used together with the marginal cost information to inform marketing mix optimization.[9]

The marketing newsletters come in various formats and have rich content focusing on either buyers or sellers. Each marketing newsletter campaign targets a designated subset of registered buyers/sellers chosen by the firm. For example, buyer-targeted newsletters encourage purchase as well as word of mouth by e-mailing existing users coupon codes that they can use or forward to their friends. Similarly, seller-targeted newsletters provide sellers with tips on pricing, product assortment, and virtual shop design. We obtain the weekly numbers of buyer and seller-targeted newsletters (as defined by the company) from the beginning of 2007 to the end of our observational period (a total of 137 observations).[10] The average number of buyer-targeted newsletters during this period is 5,895,532 per week and 655,937 for the seller-targeted ones. We include the logged values as two additional exogenous variables, LSL_t and LBL_t, in the VAR system, which leads to the following model specification:

$$\begin{bmatrix} LOS_t \\ LNS_t \\ LOB_t \\ LNB_t \\ LC_t \end{bmatrix} = \bar{\alpha} + \bar{\vartheta} t + \sum_{j=1}^{J} B_j \begin{bmatrix} LOS_{t-j} \\ LNS_{t-j} \\ LOB_{t-j} \\ LNB_{t-j} \\ LC_{t-j} \end{bmatrix} + \mathrm{H} \begin{bmatrix} LSL_t \\ LBL_t \end{bmatrix}$$
$$+ \sum_{k=1}^{4} \bar{\nu} S_{kt} + \sum_{q=2005}^{2009} \bar{\lambda} C_{qt} + \bar{\varepsilon}_t, \tag{2}$$

where H is a 5×2 matrix capturing the "newsletter elasticities" of the performance variables (numbers of new or returning buyers/sellers and commission) at their current levels. Our discussion with the firm reveals that LSL_t and LBL_t are not correlated with ε_t, because the planning of a newsletter campaign (choice of the targeted audience, design of e-mail content, etc.) takes time and is finalized before week t. Thus LSL_t and LBL_t can be justified as exogenous to the left-hand side variables. We do not include the lagged numbers of newsletters based on the fact that almost none of the users clicked on a newsletter that was sent in the previous week. In addition, we test

[9] Clearly, there are many other possible marketing actions an online marketplace can consider, such as sales contests, price promotion (delivered through coupons), or online advertising targeted at potential buyers and sellers. Based on data availability and significance for this firm, we use the case of marketing newsletters as an illustrative example, but a similar analysis can be applied to other marketing mix contexts.

[10] The firm started tracking the number of marketing letters at the beginning of 2007.

Table 5 Effects of Marketing Newsletters

Newsletter type	Commission	No. of new sellers	No. of returning sellers	No. of new buyers	No. of returning buyers
Buyer targeted	0.0368*	0.0388	0.0249*	0.0434*	0.0370**
Seller targeted	0.0026***	0.0029***	0.0017***	0.0031***	0.0023***

Note. Values are in elasticity terms.
*$p < 0.15$; **$p < 0.1$; ***$p < 0.05$.

whether the omission of LSL_t and LBL_t in model (1) leads to a misspecification problem.[11]

We start with the contemporaneous effects of marketing newsletters on the performance variables.[12] Table 5 shows the transpose of the estimated matrix H, namely, the contemporaneous newsletter elasticities of the corresponding variables. As expected, all elasticities are positive.

The finding that newsletters have positive effects on commission is particularly relevant. Assuming that the marginal cost of sending newsletters online is zero,[13] an optimizing firm should choose the number of newsletters such that sending more letters has a zero marginal effect on commission. In the case of this firm, the newsletter elasticities of commission are small but positive, indicating that the firm might further benefit by sending more newsletters each week. As expected from our results on network effects, newsletters "targeted" at one group also have positive effects on the number of users in the other group. For example, the number of new buyers may increase when seller-targeted newsletters lead to better virtual shop visibility.

We can derive the contemporaneous marginal impact of newsletters on revenues from the estimated elasticities.[14] The results are presented in Table 6. To inform the firm's marketing mix optimization, however, the contemporaneous elasticities may not sufficiently estimate the newsletters' cumulative long-term impact. When marketing newsletters help acquire sellers and buyers, these users would continue to generate value because of their network effects on other users. Put differently, the impact of a newsletter may persist even if the original newsletter no longer gets any clicks. Quantifying the total revenue contribution of sending one buyer/seller newsletter would require a procedure similar to that of the IRF simulation. The cumulative financial impact of the additional newsletter message can be simulated by tracking the long-term impact of the initial impact over time:

$$v_j = \sum_{i=1}^{5}\left(\gamma_{ji}\sum_{t=0}^{\infty}\varphi_{i5}(t)\right),$$

where $\varphi_{i5}(t)$ is the IRF function with commission as the response variable, and γ_{ji} is the contemporaneous effect of newsletter type j on endogenous variable i. The γ_{ji} parameters are identified from matrix H following the procedure in Appendix A.1 of the electronic companion. Thus the value of newsletters can be calculated by simulating a shock in the number of newsletters at time 0, which is equivalent to a *shock vector* that affects all endogenous variables contemporaneously. The cumulative impact v_j is thus a weighted average of the five CIRFs, where total commission is the response variable.

Table 6 Revenue Contributions of 1,000 Newsletter Messages

Newsletter type	Contemporaneous value ("value from clicks")	Cumulative value ("value beyond clicks")
Buyer targeted	1.7 euros	10.1 euros
Seller targeted	1.1 euros	6.4 euros

With the above-mentioned simulation approach, we can trace the long-term values created by the newsletters both directly and indirectly. We also report the estimated cumulative revenue contributions of 1,000 buyer newsletter messages and 1,000 seller newsletter messages in Table 6.

The results indicate that at the current level of newsletter intensity, 1,000 additional buyer newsletters are worth, on average (cumulatively), 10.1 euros to this firm, whereas 1,000 additional seller newsletters are worth, on average, about 6.4 euros.

The above simulation estimates the cumulative values of marketing newsletters to be about five to six times of those calculated from the contemporaneous

[11] If our basic model (1) is misspecified because of the omission of marketing mix variables, the estimates in §4 will suffer from an omitted variable bias. We estimate the VAR system with and without the numbers of marketing newsletters on the same sample starting from 2007. The values of a new seller, a new buyer, a returning seller, and a returning buyer are 302, 72, 29, and 15, respectively, without including the number of marketing newsletters; the values are 302, 81, 32, and 12 when the number of newsletters are included. These estimates are not significantly different. This suggests that the estimates in the basic model are not biased because of the omission of the marketing mix variables. This also justifies that the number of marketing newsletters is not correlated with the lagged value of the endogenous variables. All results based on model (2) are available from the authors.

[12] A caveat applies to all our findings going forward. In general, the marginal effects of newsletters should be decreasing as more newsletters are sent because consumer attention saturates. All our findings are thus limited to the current levels of newsletters and performance variables.

[13] Discussion with the firm reveals that designing newsletters involve substantial costs. Once the design is finished, however, sending more newsletters involves little additional cost. At least locally, we can assume that the marginal cost of newsletters is close to zero.

[14] According to the standard formula, $\Delta Y/\Delta X = (\bar{Y}/\bar{X})\cdot(\Delta \ln Y/\sigma_{\ln X})$, which translates elasticities into marginal effects.

elasticities. The current approach of the firm to calculate the value of marketing newsletters is to trace the click-through rates of a marketing newsletter campaign and multiply that with the direct benefits created by the buyers and sellers who have responded to the newsletters. Thus, it is assumed that an e-mail that is no longer getting any clicks ceases to generate value. If one holds this assumption, the values of buyer and seller newsletters would be fully realized in the week they are sent because most newsletters cease to get any clicks after the first week. Our results indicate that by ignoring network effects, these simple estimates significantly understate the value of marketing actions—by more than a factor of 5 in this case. Such underestimation may lead to suboptimal newsletter strategies.

5.2. Enhancing Network Effects

Our empirical analysis indicated the importance of network effects. Contributors are valuable not only because of the cash flow they generate but also because of their network value: their presence benefits the other customers and contributors, which translates into indirect contributions to the website's revenue.

There is a wide variety of actions that the website can use to enhance the network effects in the marketplace. For example, the company in our empirical study is considering improvement in the following measures:

(1) Product and Seller Review System: This allows the buyers to share their product experiences and score a seller, therefore enhancing the network effect of buyers on other buyers.

(2) Seller Referral Programs: This encourages existing sellers (especially the newly acquired sellers) to share their selling experience with their friends, in the hope of acquiring more sellers through word of mouth.

We expect such measures will make seller and buyer acquisitions even more valuable by increasing the network component in their revenue contribution. In the following simulations, we compare the value of one new seller or buyer before and after enhancing the network effects.

Formally, we define the network effect of group i on group j, α_{ji}, as the elasticity of the number of group j users in time t $(\partial N_{jt}/\partial N_{it-1})/(N_{it-1}/N_{jt})$, with respect to the number of group i users in time $t-1$. For example, α_{42} denotes the network effect of new sellers on new buyers. When, for example, $\alpha_{42}=0.5$, acquiring 1% more new sellers at time $t-1$ leads to 0.5% more new buyers joining the website at t, *all other things being equal*. When α_{42} is increased, for example, from 0.5 to 0.7, acquiring the same percentage of sellers (1%) now leads to even more buyers (0.7%) joining the website at time t.

Our simulation approach, in short, corresponds to modifying the α_{ji} structural parameters in the seller/buyer acquisition equations while keeping all other equations unchanged. This simulation methodology is along the lines of VAR-based simulations common in the economics and marketing literatures (Bernanke et al. 1997, Primiceri 2005, Sims and Zha 2006, Horváth 2003, Pauwels 2004), where a number of issues such as the Lucas critique (Lucas 1976, van Heerde et al. 2005) have been discussed. We refer interested readers to these papers for more detailed discussions. In Appendix A.1 of the electronic companion, we explain the procedure in greater detail and illustrate why modifying the parameters in the standard form, which are directly estimated, is inappropriate.

We simulate the impact of enhancing network effects by comparing the monetary values of buyer and seller acquisition (measured by CIRFs) before and after a structural parameter α_{ji} has been increased by a certain percentage. We focus on seller and buyer acquisition for the reasons stated in the beginning of §4: when the number of returning sellers/buyers is the response variable, the conceptual meaning of CIRFs is not clear.

Thus we study the impact of modifying α_{24}, α_{42}, α_{22}, and α_{44} on values of new buyers and sellers. Table 7 illustrates the results. We compare the value increases when α_{42}, α_{24}, α_{22}, or α_{44} are enhanced by 5%, respectively. To assess the outcome when several effects are simultaneously improved, we show the case when α_{24} and α_{42} are enhanced by 5% simultaneously (enhancing other pairs of effects leads to qualitatively similar results) and the case when all four effects are enhanced by 5% simultaneously. The results are qualitatively similar when the parameters are changed by different percentages.

The results reveal several findings. First, to increase the value of one group of users, it is sometimes optimal to focus on the other groups. In our example, when the firm wants to improve the value of the buyers, it should focus on network externalities between the new sellers (α_{22}) instead of those of the buyers (α_{24}/α_{44}) if the costs are comparable. On the other hand, when we increase the network effects of one type of users, the value of this type of users will also increase the most. For example, when we increase α_{24} or α_{44} (new buyers' network effects on others), the value of buyers will increase by 8.5% and 6.4%, respectively, more than the increase in the value of sellers (3.7% or 2.5%).

Moreover, enhancing the network effects in different directions are complementary decisions.[15] For

[15] See Topkis (1998) for a formal definition and implications of complementarities in actions.

Table 7 Enhancing Network Effects

	Before enhancing network effects	Enhancing buyers' network effects on sellers (α_{24}) by 5%	Enhancing sellers' network effects on buyers (α_{42}) by 5%	Enhancing sellers' network effects on sellers (α_{22}) by 5%	Enhancing buyers' network effects on buyers (α_{44}) by 5%	Enhancing both α_{42} and α_{24} by 5%	Enhancing all four effects by 5%
Value of one new seller	242	251	246	308	248	267	410
Value of one new buyer	94	102	95	105	100	105	145

Note. All numbers are in euro terms.

example, enhancing α_{24} by 5% increases the value of a seller by $251 - 242 = 9$ euros. Enhancing α_{42} by 5% increases the value of a seller by $246 - 242 = 4$ euros. Moreover, enhancing both α_{42} and α_{24} by 5% simultaneously will increase the value of a seller by $267 - 242 = 25$ euros, which is greater than $9 + 4 = 13$ euros. We obtain similar results when other pairs of network effects are improved simultaneously. These findings have clear managerial implications. The C2C firm in our context has the options of implementing seller referral system and product review system. Because these systems tend to focus on different types of network effects, the marginal return from implementing or improving each system increases when other systems are already implemented or improved. Taking cost into account, when the cost functions are convex, the firm should focus on the most profitable network effect (sellers on sellers in the C2C website we study) when cost is low and "spread" out its investment when the cost becomes higher.

Finally, as expected, increasing network effects overall leads to a large increase in the values of seller and buyer acquisition. In the C2C website we study, enhancing sellers' network effects on other sellers represents the most profitable direction.

6. Further Analyses and Robustness Checks

The analysis above is based on a VAR model estimated from aggregated data over the entire observation period. In this section, we present further analyses that examine the evolution of VAR estimates over time and the heterogeneity across product categories. Although the results about time evolution and cross-category heterogeneity are of their own interest, these analyses also serve as robustness checks of the qualitative findings from our basic model.

6.1. Time Evolution of Values and Network Effects

We first examine whether the revenue contributions of buyers and sellers change over time during our observation period. To answer this question, we estimate the VAR model on 100 consecutive time windows, with the first time window corresponding to the 1st to the 101st observations (weeks) and the last time window corresponding to the 101st to the 201st observations. This process is similar to the moving window analysis in Pauwels and Hanssens (2007). The procedure yields 100 different VAR estimates, with which we can perform IRF simulations to track the evolution of seller/buyer values over time. We plot the revenue contributions of new or returning sellers/buyers against the number of time window in Figure 1.[16]

Figure 1 suggests that our qualitative findings (that sellers make higher revenue contributions than buyers and that acquisition makes higher revenue contribution than retention) remain valid over time. Pairwise significance tests by Monte Carlo simulation confirm that the estimated revenue contributions are not significantly different in any two time windows. The qualitative finding that new sellers bring in the most number of other sellers and buyers is also robust over time (details not shown for brevity). The company considers these findings reasonable, because 2005–2009 has been a period of stable growth for the website.

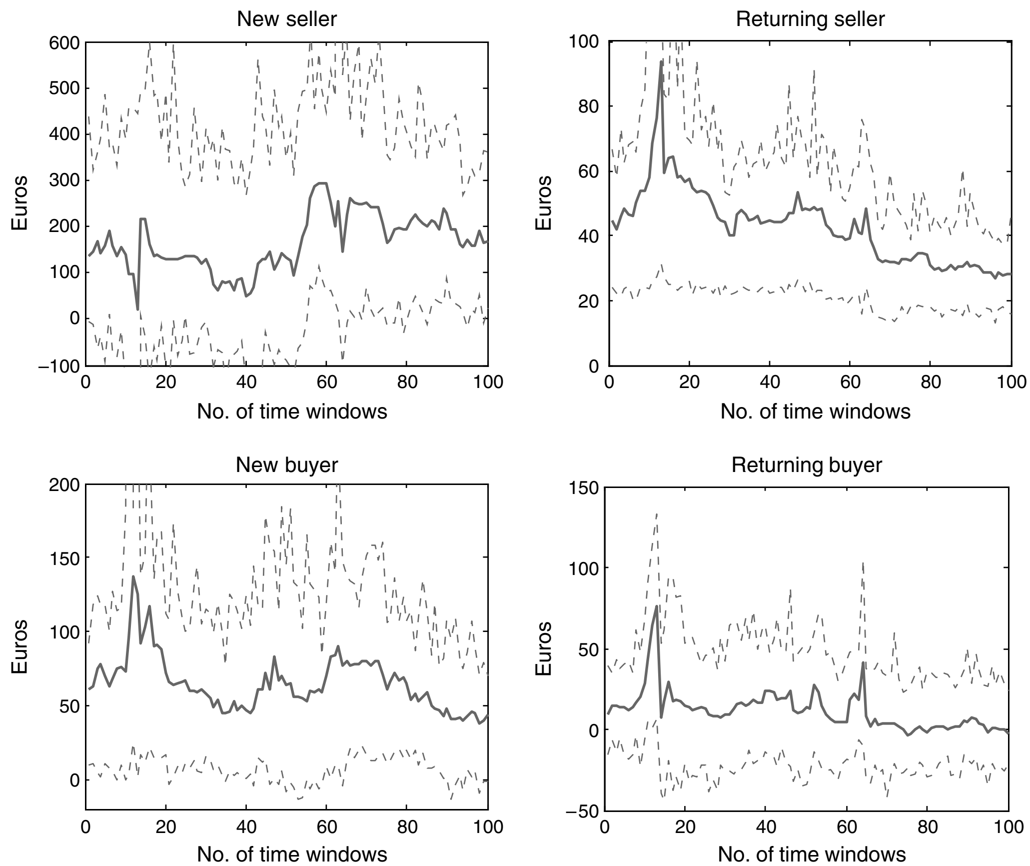
6.2. Segment-Level Analysis

Unobserved heterogeneity and aggregation bias is a particularly important concern for dynamic models such as VAR based on aggregate data (see Pauwels et al. 2004 for a review). To explore this issue, we perform a segment-level analysis to examine the relative values of buyers/sellers in different product categories. We estimate VAR models for six different product categories. We report the estimated revenue contributions in Table 8.

Overall, the results indicate that there is considerable heterogeneity in the value of buyers and sellers across product categories. Yet our main results qualitatively hold in all segments. In particular, the revenue contribution of sellers is higher than that of buyers, and the revenue contribution of new sellers/buyers is higher than that of returning sellers/buyers. We test these via Monte Carlo tests with 250 replications. The results are shown in Appendix A.8 of

[16] The relative small sample size and the large number of parameters give less efficient estimates. We plot the 95% confidence interval derived from Monte Carlo simulation for each value of CIRF.

Figure 1 **Time Evolution of Revenue Contributions**



Note. The solid lines correspond to the estimates, and the dashed lines correspond to 95% confidence intervals.

the electronic companion. Note that unlike the results from the basic model, new buyers are not necessarily more valuable than returning sellers across all product categories.

A cautionary note applies when we try to interpret the estimated values. The segment-level analysis neglects any between segments effect, and the estimated value for each segment should not be directly compared with the results obtained from the main model.

7. Concluding Remarks

In this paper, we take a first step in studying the "content contributor management" problem for a UGC website. We developed an empirical framework based on persistence modeling techniques and applied it to the context of a C2C marketplace. The empirical results indicate how the network effects, which we quantify, affect the valuations of buyers and sellers. The most valuable users also tend to have the largest network effects on other users. For example, for the particular company we study, acquiring one new seller is worth, on average, about 20 times more than retaining one existing buyer and about 6 times more than retaining one existing seller. In general, network effects constitute more than 80% of the total revenue contributions of new sellers and buyers. The simulations shed light on the firm's marketing mix choices as well as enhancing network effects decisions. For example, we find that for the particular company we study, measuring the value of e-mail marketing campaigns using only the immediate cash flow of such campaigns (for example, when receivers click on links in the e-mails they receive) can underestimate by more than a factor of 5 the value of such campaigns. We also find that if this firm wants to improve the value of its buyers, it should focus on network effects between its sellers instead of those between its buyers. For example, when costs are comparable, a "seller

Table 8 **Segment-Level Analysis**

Product category	New seller	Returning seller	New buyer	Returning buyer
Main model (as in Table 2)	242*	45*	94*	11
Books and magazines	248*	45*	65*	−1
Videos and CDs	366*	52*	41*	−0.8
Computer and peripheral	238*	82*	27*	13*
Household goods	173*	74*	13*	6*
Furniture	125*	64*	25*	6*

*$p < 0.05$.

referral program" focusing on sellers can increase the buyers' value more than a "product review system" that focuses on buyers. Our methodology allows UGC companies to reach more sound, and possibly unexpected, managerial conclusions through a better measurement of all relevant quantities.

Numerous directions for future research are possible. First, obtaining data over the entire life cycle of a website can lead to additional insights on how the values of seller/buyer acquisition or retention evolve over the stages of a website's life cycle. The values of sellers and buyers may differ considerably for a young website and a more mature website. Second, although our approach measures the magnitudes of overall network effects, further disentangling the different sources of network effects (such as word of mouth, observational learning, product assortment enrichment, direct social interaction, etc.) can shed light on the effectiveness of more specific managerial actions. For example, when is a seller scoring system preferred to a product review system as an instrument to enhance buyer–buyer and buyer–seller network effects? Finally, using data from other UGC firms could allow us to study the generalizability of our results or to extend and improve on them. In addition, alternative methodologies (such as diffusion models or controlled experiments) can be used to assess the impact of specific managerial actions.

Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at http://mktsci.journal.informs.org/.

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