Network-induced Lock-in

A choice experiment examining social-network-caused online user inertia

Jan Broel–Plater*

Supervisor: Professor Håkan J. Holm

Bachelor's Essay
Department of Economics, School of Economics and Management
Lund University, Sweden

October 3, 2008

Abstract

This essay examines whether there is empirical evidence of greater switching costs, and consequently greater lock-in effects, in the choice between online services bearing social characteristics than in the choice between services lacking such social network characteristics. An online choice experiment was performed where respondents were asked to choose between consumption bundles consisting of either web search engines or social network websites. The dataset was evaluated using a chi-square test and a probit regression analysis to check for correlations with demographic variables. The results show that switching costs are significantly higher for social network websites, and that the probability of switching increases with age.

*The author would like to acknowledge the patient assistance of Professor Håkan J. Holm and Lina Haskå.

Contents

1 Introduction

The last decade has witnessed the advent of web communities – online social networking services where users communicate and collaborate with steadily growing numbers of participants – and along with it, soaring valuations of the providing companies. One prominent example is the Facebook sale in October 2007, where a small slice of the company was bought by Microsoft at a price implying a hypothetical fifteen billion dollar value for the entire corporation. Perhaps even more illustrative is the corresponding per-user price tag of 300 dollars while the yearly per-user revenue was estimated to little more than a meagre two dollars.

Although the Facebook deal was an extreme of sorts, one may easily find other lower scale examples that bear important similarities. Nonetheless, what is evident from the fact that Facebook was spawned by a 20-year-old and in two years became the greatest threat to MySpace, the largest market player, is that market entry was exceptionally easy due mainly to a relatively low level of technical sophistication.

Bearing this in mind, together with the fact that substitution of communication services online could be considered a fairly trivial task, the remarkable valuations raise questions about the rationale behind such prices. One possible answer to this question can be found in economic theory, which implies that the social dimension of this class of services generate a lock-in effect and thus higher prices.

2 Purpose

The focal question in this essay is whether there is empirical evidence of greater switching costs, and consequently greater lock-in effects experienced by users, in the choice between online services bearing social characteristics than in the choice between services lacking such social network characteristics.

3 Method

3.1 Stated Preference methods

For valuation of goods, two options are commonly used (Alpizar et al. 2003). *Revealed preference* methods, such as primarily the hedonic pricing method and the travel cost method, gather price data from observations of revealed actual markets and consumer behaviour. In circumstances where such information for any reason is not available, as is the case with non-market goods, the use of revealed preference can prove difficult and even impossible in some cases.

Conversely, *stated preference* methods have been used for valuing non-market goods for quite some time, by enquiring individuals for their actions in hypothetical situations. A frequent area of application of stated preference surveys is the valuation of public goods, which is often the issue in environmental and health economics, and examples include assessing the value of pollution free living or the value of saving a life.

The two dominating stated preference methods are *contingent valuation* (CV) and *choice experiments* (CE). With the widely used CV method, conceived by Ciriacy-Wantrup (1947), survey makers ask participants to state their willingness to pay for a certain good. The method has been criticised for, among other things, the hypothetical nature of the method, and the associated incentive for individuals to exaggerate their willingness to pay (Diamond and Hausman 1994, Hanemann 1994). CE provide an alternative means to valuation. Willingness to pay is implicitly derived by letting subjects repeatedly make trade-offs by choosing a preferred bundle from prearranged choice sets in different price situations, and reduces the bias susceptibility attributed to the CV method. One important CE advantage is the ability to extract a greater amount of choice data from each subject, while CV respondents may face binary options such as choosing loss or gain of a good. CE also make possible the implementation of internal consistency tests (Hanley et al. 1998, Alpizar et al. 2003).

Another stated preference issue, primarily associated with contingent valuation, is question order bias (Bishop and Heberlein 1986, Mitchell and Carson 1989). Studies have shown that in some cases valuations of goods depend on the order in which the willingness to pay for a good is requested (Samples and Hollyer 1990).

With non-market goods however, both stated preference methods prove simple and inexpensive in comparison with revealed preference methods.

3.2 Previous choice experiments

Kagel and Roth (1995) mention some important choice experiments for market goods. Thurstone (1931) let subjects hypothetically choose between different bundles of hats, shoes and coats in an attempt to chart individual indifference curves. By combining pair data from hats versus coats and hats versus shoes choices, Thurstone managed to predict the outcome of the shoes versus coats results fairly accurately. Wallis and Friedman (1942) criticised the study and argued that hypothetical choices with no consequences in received utility would inevitably result in erroneous data. In light of this critique, Rousseas and Hart (1951) designed their experiment with choices of various amounts of eggs and bacon strips so that the chosen bundle was obligatory to consume in order to make the experiment more concrete and realistic (Kagel and Roth 1995). The next generation of choice experiments, Mosteller and Nogee (1951) for instance, followed in the light of the expected utility theory by von Neumann and Morgenstern (1944), aiming to investigate the mechanisms of individual choice under uncertainty. Regarding model application on non-market goods, noteworthy examples in environmental economics are Adamowicz et al. (1998), Ryan and Hughes (1997) and Layton and Brown (1998) in health economics.

4 Networks

4.1 Network effects

When using the term *economies of scale*, what is usually meant is supply-side economies of scale; situations where average production costs decline as quantity is increased, thus lowering unit costs with a greater scale of production. In contrast, demand-side economies of scale describe circumstances where synergies or efficiency increases occur outside the producing entity. Networks are instances of demand-side economies of scale because additional user adoption gives complementary payoff (network externalities in other words) to existing users. That is, the value of connecting to a network

depends on the number of other people already connected to it (Katz and Shapiro 1994, p.96).

Many products display network characteristics to some extent today; telecommunications, computer platforms, camera systems, home entertainment video systems and so forth. In these cases, the products or services would be considered more or less useless in a standalone setting. While for instance the 3G cell phone standard might provide new superior communication functionality to its adopters, the first group of consumers to buy 3G phones are likely to be disappointed because not only will the coverage probably be bad, there will also be a distinct lack of users to communicate with. Similarly, users of the Linux operating system do not enjoy an abundant amount of auxiliary software as do Windows users, again due to a smaller network surrounding the product and fewer software producers.

From a producer's point of view, *positive* and *negative feedback* in network economies are double-edged swords that may easily change market outcomes and are driven by "herd" mentality, displaying collective consumer expectation of the survival and growth aptitude of goods or brands. Since the value of the network is directly affected by the number of nodes attached to it, a slight advantage in a market bearing network characteristics can be vastly amplified by raised expectations and the perception of a market leader. In the choice between two video systems equal in quality and price, such as for example the Blu-ray and HD DVD systems, consumers opt for the system with the greatest chance of wide adoption since in any other case they would be left with expensive hardware but no discs to play. When a good catches an upward momentum in this fashion, it is exposed to positive feedback. On the other hand, negative feedback is the opposite effect amplifying the decline of the disadvantageous competitors.

The feedback effects create a volatile setting for network-based products, making the market "tippy" (Shapiro and Varian 1998, p.176). Market shares tend to tilt in such a way that under some conditions companies riding a wave of positive feedback may obtain a monopoly-like position while at the same time smaller competitors might face business failure. The tippiness of network markets is often observed in history; as Blu-ray gradually gains dominance in the high definition video market, the VHS standard was once able to gain an advantage against the technically better Betamax system. On the home PC operating systems market Microsoft's Windows holds a 99 percent share after battling with IBM's OS/2 for domination in the early 90's. (Shapiro and Varian 1998)

4.2 Networks and switching costs

Lock-in is faced by consumers and users when the benefit an individual enjoys from switching from one product or service to another is less than the cost of switching (Shapiro and Varian 1998) – in which case the individual is not likely to switch. Following the previous example of operating systems, switching from Windows to Linux often requires investments in time (learning how to use the system) and money (buying additional software) – switching costs that for many individuals are likely to exceed the potential gains achieved from switching, and are hence locking them into the Windows platform.

What is particularly interesting about lock-in in the context of web services is the way the lock-in effect is measured. *Mass-market lock-in* is calculated by multiplying the per-user switching cost with the number of customers. This allows for great lock-in value even if the per-user switching cost is considerably small, if compensated by a large market share (Shapiro and Varian 1998, p.108). Also, because the formula used for modelling network externalities[1] is non-linear, the switching of entire networks become increasingly difficult with the number of nodes: "convincing ten people connected in a network to switch to your incompatible network is more than ten times as hard as getting one customer to switch." (Shapiro and Varian 1998, p.184)

4.3 Networks – Game theory

Game theory provides insight in the analysis of the behaviour exhibited by network users, and the coordination class of games is specially suited for this purpose. As indicated in section 4.1, maximum payoff is obtained when some sort of coordination is obtained. Consequently, the class of games that describe these conditions are known as *coordination games*, characterised also by the existence of multiple Nash equilibria. A suitable example of a coordination game is displayed in normal form in table 1;

[1] Metcalfe's law states that the number of unique connections in a network with n nodes is equal to $\frac{n(n-1)}{2}$ (Shapiro and Varian 1998).

Table 1: "Battle of the Sexes".

		Player 2	
		A	B
Player 1	A	$10, 5$	$0, 0$
	B	$0, 0$	$5, 10$

The well-known battle of the sexes game[2] has two pure strategy Nash equilibria (A, A) and (B, B), and one equilibrium in mixed strategy. In this case, the mixed strategy gives that each player pursues his or her favourable option with a possibility of $^{10}/_{15}$ (Varian 2006, pp.522). To describe situations where social adherence or following standards is rewarded, another oft-used model is the related *pure coordination* game[3]. Contrary to the battle of the sexes, it does not display the characteristic of a conflict of interests.

The greater payoff obtained in both games from conforming to standards is in effect positive network externalities. Especially the battle of the sexes game applies well to online communities as it is possible that users choose a service not entirely based upon their preference, but seeks to maximise the possibility of interaction with established friends. Optionally, the user cares more about meeting new people, but since the possibility of finding friends is presumed to be ubiquitous it would presumably be possible to obtain *equal or greater* payoff by choosing the service most popular with the existing friends. This in turn motivates the use of this game over the pure coordination game. With both games, however, it is difficult to forecast the outcome, and "The problem, in practice, is to develop mechanisms that enable this coordination." (Varian 2006, p.524)

4.4 Networks and online services

Unlike some of the examples mentioned above, neither online communities nor search engines display the binary win all/lose all characteristic of a technology standard setting good where demand for variety is exceptionally low (Shapiro and Varian 1998). The extent of feedback effects should thus be lesser in comparison. It is nevertheless reasonable to argue that due to the

[2]The game was originally supposed to portray a couple choosing their evening distractions or a variation on this theme. While the husband prefers football to opera, and the wife prefers opera to football, they both prefer to spend time together.

[3]As in the illustrated example, but with $(A, A) = (10, 10)$ and $(B, B) = (10, 10)$.

larger demand-side economies of scale, one may expect greater inertia in the case of online communities than with search engines. Since a user's array of connected friends and the interaction with them is unquestionably the foundation for community activity, switching to another community would in most cases decrease the payoff received from participating in the network because the herd of friends are not likely to automatically follow. The switching cost in this situation, and ultimately a source of lock-in, consists primarily of decreased value of use in addition to the effort of coordination mentioned in the previous section. In some cases, Facebook in specific, further lock-in is created by the bestowment of prehensile user agreements upon users, seizing rights to uploaded material. A recent trend in the community business is the standardisation of online account data and application platforms[4]. While these techniques do improve user mobility, they are not sufficiently lessening the effort needed to move a person's entire social network to another service.

With search engines, the payoff stems mainly from the ability of the service to efficiently find information relevant to the user's query. Since this quality is essentially independent of the number of users the service flaunts, one should expect no significant lock-in in the choice between two equally efficient search engines owing to network externalities.

Certainly, switching search engines are likely to involve costs as well, but the overall switching costs ought to be of moderate extents in comparison to online communities. The bulk of the costs are sustained from getting acquainted with a new interface and a new set of functionality – a fairly trivial task considering the uniformity of these services. This, hence, would imply a relatively smaller expected switching cost for search engines in the survey.

[4]Such as OpenID and OpenSocial for instance.

5 Experimental design

The survey consisted of two questionnaires, Q_1 and Q_2. Whereas Q_1 had the respondents choose between two renowned search engines, Google and Microsoft Live, Q_2 concerned social networking websites Facebook and MySpace. Both questionnaires were initiated with a set of common closed-ended questions regarding background and demographic variables. The initial questions are given in table 2.

Table 2: Survey questionnaires.

Question	Q_1	Q_2	*Choices*
1	What is your gender?		female, male
2	What is your age?		15-100
3	How long have you been using Google Web Search?	How long have you been using Facebook?	1 (never), 2 (less than three months), 3 (between three months and a year), 4 (more than a year)
4	How long have you been using Microsoft Live Search?	How long have you been using MySpace?	1–4 as above
5	Which search engine do you use most often?	Which social networking website do you visit most often?	1 (Google), 2 (Yahoo), 3 (MS Live), 4 (Altavista), 5 (Other) and 1 (Facebook), 2 (MySpace), 3 (LinkedIn), 4 (Friendster), 5 (Other)
6	How would you rank the similarity of functionality of Gooogle Web Search and Microsoft Live Search?	How would you rank the similarity of functionality of Facebook and MySpace?	1 (not similar at all), 2 (not particularly similar), 3 (there are some similarities), 4 (rather similar), 5 (very similar), 6 (don't know)

For the collection of the main price-quantity data, several instances of the following question were displayed, where the price parameters were changed according to a pre-determined pattern. For the first questionnaire regarding search engines;

> Given that you have \$5 to spend over a week, doing one search on Google costs ¢10 (\$0.10]) and doing one search on Microsoft Live costs ¢10 (\$0.10). How would you choose to spend your time?

For the second questionnaire regarding social network services;

> Given that you have \$5 to spend over a week, visiting Facebook.com costs ¢10 (\$0.10) a minute and visiting MySpace.com costs ¢10 (\$0.10) a minute. How would you choose to spend your time?

The prices were selected in such a way that the price ratio $^{p_1}/_{p_2}$ between the two services would at first increase by making the first service relatively more expensive and then decrease by making the second service more expensive. For each of these questions, the respondents were presented with a menu of six pre-determined consumption bundles, all reaching the budget constraint of five dollars. The complete choice matrix is available in appendix A. An example of this menu is given in table 3.

Table 3: Survey choice menu, price ratio equals one.

Bundle	*Google Searches*	*MS Live searches*
1	50	0
2	40	10
3	30	20
4	20	30
5	10	40
6	0	50

An effort was made to simplify comprehension of the questions and to minimise the time of answering. Sliders[5] were at first considered as the primary

[5]A graphical user interface controls with which a user may set a value by moving an indicator in a horizontal fashion.

means of collecting respondent input, as they would allow subjects to compose their preferred unique bundles in every price setting. The intention was to eliminate random choices and as far as possible promote reflection to each answer. After initial test rounds, however, the sliders were rejected in favour of discrete choice matrices operated by radio buttons, due to the complexity and time-consuming nature of the interface that had to be explained thoroughly before answering. The number of alternatives available to the respondents was also reduced after a second test round using the radio button interface.

The survey was published on a small community not unlike Facebook, and to motivate partaking and completion of the survey, token money applicable as payment on the community was offered to successful respondents. Besides being a time and cost effective method, another motive for carrying out the survey online was to attract typical heavy web users.

6 Quantitative methodology

In order to process the data set in a meaningful way, a reasonable definition needs to be established of when a switch is said to occur. The chosen option involves regarding the cases where the entirety of the budget is spent on one service where the price ratio is equal to one. The switching point is then defined as the point where any level of adoption of the other service takes place as the price of the first chosen good is gradually increased. This method proves advantageous in comparison to two other plausible tactics.

Examining respondents who move from choosing one hundred percent of their budget on one service to one hundred percent on the other service is another option. While this stringent approach offers an attractively distinctive classification of switches, it radically decreases the number of useful observations. Conversely, one might consider respondents "sliding over" from predominantly spending their budgets on one service to the other. Still, the credibility of this option is questionable because it is unlikely that these circumstances are perceived as a switch from the perspective of the survey subjects. By simply altering consumption quantities, subjects do not have to consider the effort of adapting to a new service, learning the functionality and subtleties of it. In the case of online communities there would be no need for finding a new network of acquaintances. Hence, respondents are unlikely to experience any noticeable lock-in with this definition. The chosen

option thus remains the best line of attack, as it does indeed entail first-view adoption of a service. For social networks, this definition still requires users to follow a registration procedure on a website where they presumably do not have an existing social network.

With this distinction at hand, it is possible to compute the switching points by traversing the nine price-quantity observations of each respondent. Observation data from subjects preferring the second alternative was inverted in order to produce a complete set of switching points ranging from 1.1 to 5. The answers of respondents that exclusively spent their budget on one service at a price ratio of one, and later chose to increase their consumption of the other service as it got more expensive, were considered as kinks resulting from spurious answers and consequently discarded.

The principal statistical analysis of this study aimed to find differences in switching costs between the two classes of services. It consisted of a chi-square test of the observed frequencies of the different switching price ratios, ranked for each subject with an ordinal scale ranging from one to five (where a higher number denotes a higher price ratio, the number five accordingly signified the absence of a switch).

In order to examine which variables (age, sex, similarity and questionnaire number) affect the probability of a respondent switching service, a probit analysis was also used. All variables could be assumed to be independent.

7 Results

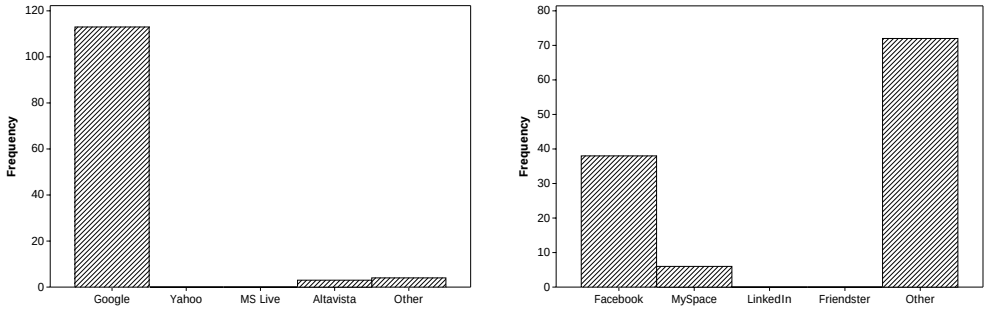
7.1 Overview

Excluding incomplete and duplicate answers, the survey yielded 120 answers from the search engine questionnaire Q_1, and 116 from the community questionnaire Q_2. With further filtering of unreasonable answers, the number of answers was reduced to 111 for Q_1 and 100 for Q_2. Respondent demographics in terms of gender and age are quite characteristic for heavy users of online services – the median subject was a 20 year old male. It could be parenthetically pointed out that of those who responded to Q_2, there was a larger share of female respondents than in the survey as a whole. Descriptive statistics are presented in table 4.

Table 4: Descriptive statistics. *: Filtered for "don't know" answers. The meaning of the numeric values in variables "Time used", "Most used" and "Similarity" is explained in table 2.

Variable	*Questionnaire*	*Mean*	*StDev*	*Median*
Age	1	21.0	4.4	20
Sex	1	1.6	0.5	2
Time used Google	1	3.7	0.8	4
Time used MS Live	1	1.7	1.0	1
Most used service	1	1.1	0.7	1
Similarity*	1	3.1	1.4	3
Age	2	21.4	4.7	20
Sex	2	1.5	0.5	2
Time used Facebook	2	2.1	1.0	2
Time used MySpace	2	1.7	1.0	1
Most used service	2	3.5	1.9	5
Similarity*	2	2.5	1.2	3

In Q_1, Google's dominance becomes apparent. Nearly all respondents had been using this search engine for more than a year, whereas a majority had no experience with Microsoft Live Search. The opinion on similarity between the compared services, on a scale from one to five, averaged 3.1. Even if this number indicates a relatively high perceived similarity, especially in comparison with Q_2, a stunning 94% of the respondents chose Google when asked which search engine they used most often. This is illustrated clearly in figure 1.

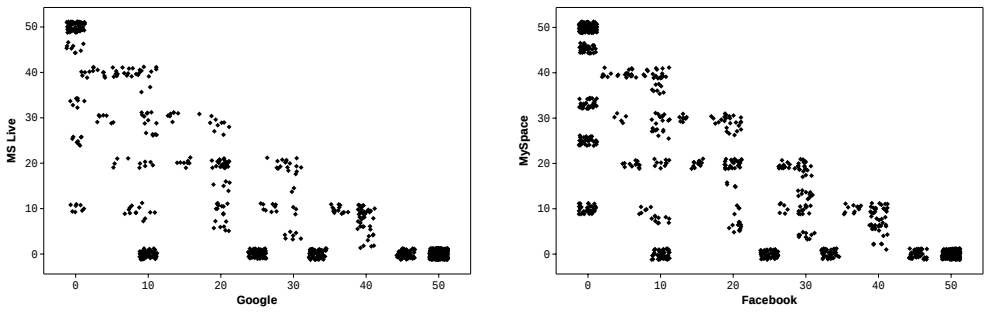


(a) Q_1 (b) Q_2

Figure 1: Most used services in surveys Q_1 and Q_2.

The two social networks compared in Q_2 were ranked less similar in comparison with a mean value of 2.5. Among the social networks, frequent users of Facebook clearly outnumber MySpace users, but the frontrunner is the "other" alternative with a 62% share among respondents. A reasonable explanation for this is that the survey was published on a web community not unlike Facebook or MySpace, modulo much smaller and niched towards dating.

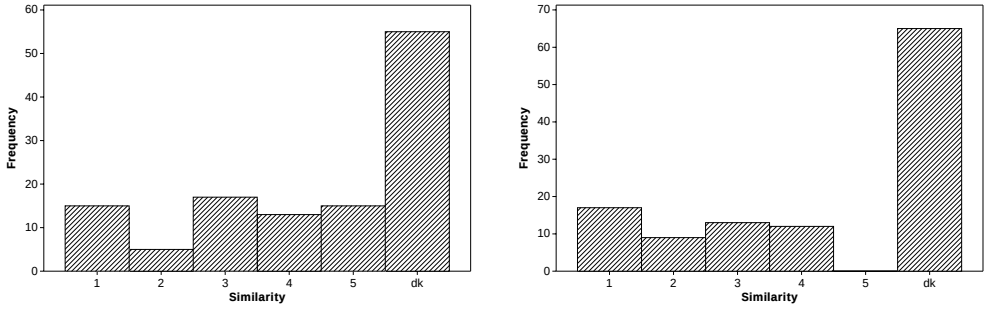
The trade-off observations collected from the price-quantity question batch are plotted for the two questionnaires in figure 2. Each dot depicts a chosen bundle of consumption at one particular price ratio. From the large number of observations for bundles made up of only one good, it is obvious for both classes of services that subjects find it difficult to trade off their preferred service.



(a) Q_1 (b) Q_2

Figure 2: Choice maps.

Figure 3 shows that there is little difference in the perceived similarity between on the one hand Google and MS Live, and on yet the other hand Facebook and MySpace.



(a) Q_1 (b) Q_2

Figure 3: Histogram (a) displays the perceived similarity between Google and MS Live, and between Facebook and MySpace in histogram (b).

7.2 Chi-square switching point analysis

To examine the difference in switching point levels between the two questionnaires, the following hypothesis is stated;

$$H_0 \quad : \quad \text{There are no significant differences in switching points depending on the class of services.}$$

The switching point frequencies are presented in table 5 below. These numbers render a chi-square test statistic of 14.347 with 4 degrees of freedom. This in turn yields a p-value of $p = 0.006$, significant at 1%. The null hypothesis is consequently rejected as there is statistical support for the alternative hypothesis, albeit three out of ten cells shows expected counts lower than what is prescribed for the model[6].

[6]Körner and Wahlgren (2000) states that no more than 20% of the expected frequencies should be below 5.

Table 5: Switching point frequencies. Expected frequencies in paranthesises.

Questionnaire	*1.1*	*1.5*	*2*	*5*	*Never*	$\sum$
Q_1	11 (9.83)	12 (8.19)	7 (3.82)	7 (5.46)	52 (61.70)	89
Q_2	7 (8.13)	3 (6.81)	0 (3.18)	3 (4.54)	61 (51.30)	74
$\sum$	**18**	**15**	**7**	**10**	**113**	**163**

To ameliorate this analysis, switching points ranging from 1.1 to 5 are pooled and compared to the non-switching observations in a second chi-square test. The results are displayed in table 6.

Table 6: Pooled switching point frequencies.

Questionnaire	*Switches*	*Never switches*	$\sum$
Q_1	37 (27.30)	52 (61.70)	89
Q_2	13 (22.70)	61 (51.30)	74
$\sum$	**50**	**113**	**163**

With one degree of freedom and a test statistic of 10.949, these frequencies render a p-value equal to 0.001. Also this p-value is significant at 1%, but it does not share the weakness of the previous analysis. There is, hence, strong evidence to believe there is a difference in the way the respondents chose between search engines and social communities[7].

The mean values in table 7 show that switching points in the second questionnaire concerning social network services are greater on average. Combining this result with the p-value from the previous chi-square analysis, it is evident that switching points are significantly greater for social network services than for search engines.

Table 7: Switching points – descriptive statistics.

Questionnaire	*N*	*Mean*	*StDev*	*Median*
Q_1	89	3.865	1.524	5
Q_2	74	4.459	1.284	5

[7]A third chi-square test was applied and indicated no significant sequencing errors in the generated data with p=0.064.

7.3 Probit regression analysis

In addition to the chi-square analysis, the data set is analysed using a probit regression analysis with the intention of locating possible correlations. The test also provides a corroborating test of the main hypothesis. Thus, the questionnaire number is added as a parameter in the probit model, which is stated as follows;

$$\begin{aligned} z &= \beta_1 + \beta_2 \cdot age + \beta_3 \cdot sex + \\ &\quad \beta_4 \cdot similarity + \beta_5 \cdot questionnaire \end{aligned}$$

Used with the standard cumulative function, the z-value on the left hand side of the equation produces a probability prediction of a subject to switch services.

Table 8: Probit analysis parameter coefficient estimates.

Variable	*Estimate*	*StdErr*	*p*
Intercept	-0.563	0.756	0.457
Age	0.072**	0.025	0.004
Sex	-0.227	0.229	0.323
Similarity	-0.008	0.061	0.896
Questionnaire	-0.761**	0.227	0.001

The probit analysis results are displayed in table 7.5. With a p-value of 0.001, the questionnaire parameter is significant at 1%, which gives further strength to the alternative hypothesis as stated in the previous section. That is, the answering of the questionnaire regarding social network services decreases the z statistic by 0.761 which in consequence significantly lowers the probability of a switch. The age parameter is also significant at 1% with a p-value of 0.004. No other significances were noted.

The goodness-of-fit results show that the described model fits the data significantly better than an intercept-only model with a p-value of 0.001. Three pseudo R^2 measurements are also provided; Cox and Snell returned 0.116, Nagelkerke 0.163 and McFadden 0.099.

The analysis shows that for a median subject, changing the compared class of services from search engines to online communities, the probability of switching decreases with approximately 28%[8]. By increasing the age variable with one year, switching probability increases with 2.7% for search engine respondents and 1.5% for community respondents.

8 Discussion

This study shows that network effects cause greater switching costs, and as a consequence greater lock-in, for users of online communities in comparison to search engines. Two different analyses led to this conclusion. First, a chi-square comparison showed that survey respondents facing a choice between Facebook and MySpace have significantly greater switching points than those facing a choice between Google and Microsoft Live Search. Second, a probability model was presented aiming to determine the influence of the included parameters (age, sex, similarity and service type) on the switching probability. The analysis showed that for the median subject, choosing between social network services renders a decreased probability of switching by approximately 28%.

The coordination effort mentioned in section 4.3 is also likely to induce already positioned users to remain with their favourite service at almost any cost, and it was confirmed that subjects are strongly reluctant to move away from their favourite habitat.

Interestingly, the age parameter also indicated significance at 1%. Survey data implies that regardless of the social attribute of a choice between two services, switching inertia decreases with age.

A possible weakness of the study is the meagre perception of likeness among those who did rate the services. 51% chose either the "Not similar at all" or the "Not particularly similar" option in Q_2 (31% in Q_1). It would of course be preferable if the respondents regarded the services as perfectly interchangeable as it would isolate the social or non-social characteristics of the compared goods, but such circumstances in this type of market rarely occur in practice. At the same time, the similarity distributions between the

[8] $\frac{dp}{dx_i} = \frac{dF(t)}{dt} \cdot \frac{dt}{dx_i} = f(\beta_1 + \beta_2 x_2 + \ldots + \beta_n x_n)\beta_i$ where $f(\cdot)$ is the standard normal probability density function. (Hill et al. 2001)

two classes of services do not diverge in any radical way. Ideally, this would imply that similarity can be ruled out as a factor driving switching costs, yet it cannot be excluded they are not affected by the actual difference. Furthermore, subjects intuitively ought to be more likely to switch with increased ease of substitution. The similarity measure was therefore assumed to increase switching probability, but this turned out not to be the case.

It may still be tempting to argue that the lock-in is mainly generated by dissimilarities between the services, and for social communities there are indeed some differences. Facebook has drawn attention to its innovative application interface, letting anyone create and extend the functionality of the website itself. MySpace, on the other hand, has found a niche in music, encouraging users to upload their own songs and create homepages for their music groups. Such characteristics, along with the more obvious graphical layout differences, obviously promote the perception of dissimilarity. At the execution time of the experiment, however, MySpace had already launched its own version of an application interface (McCarthy 2008), limiting the functionality gap between the services. The main online activities, such as chatting, file sharing, participating in user groups etcetera, are available with both Facebook and MySpace. Thus, a majority of the online activity appears to be substitutable. Much the same can be said about the search engines in the study. Both Google and MS Live Search also satisfy the same basic need, finding something a user is looking for on the World Wide Web. They both use essentially the same technique for interpreting user input, figuring out what the user wants to find, and for finding it.

An interesting question is whether respondents tend to, in an ideological fashion, exaggerate the dissimilarity in order to justify their choice of online community or search engine. A possible explanation for such behaviour could very well be network effects in that users are motivated to endorse the technology they themselves use in order to maintain and raise the value of their "investment" in it.

To summarise, the subjects of this study were inclined to assign low similarity ranks to the services, yet these ranks had no effect on their likelihood of switching. This behaviour could be explained if the *revealed* (unconscious) perception of similarity is greater than the one stated.

The borderline p-value in the sequencing error test showed that there was no significant order bias. Another issue is random answers. Faced with a hypothetical question concerning two web services, with a good chance

of unfamiliarity of either one of them, it is likely that respondents exhibit a certain degree of uncertainty in their answers as the choices individuals make are rarely one hundred percent premeditated – many actions stem solely from instinct or habit and possibly even more so in a hypothetical situation with invented prices for a good most people would take for granted as free. One example of this problem is the situation where subjects explicitly choosing, for instance, Facebook as the service they spend the most time on, yet select the one hundred percent MySpace alternative in a situation where the price quote equals one. Although observations such as these are due in many cases to the method, the revealed preference option cannot be considered a realistic alternative in this context. While a setting such as a web café could provide an environment where payment for online services is normal, motivating the price differentiation of services would remain difficult. Such a study would also involve considerably higher costs.

References

Adamowicz, W., Boxall, P., and Williams, M. (1998). Stated preference approaches for measuring passive use values: Choice experiments and contingent... *American Journal of Agricultural Economics*, 80(1):64–76.

Alpizar, F., Carlsson, F., and Martinsson, P. (2003). Using choice experiments for non-market valuation. *Economic Issues*, 8:83–110.

Bishop, R. C. and Heberlein, T. A. (1986). Does contingent valuation work? In Cummings, R. G., Brookshire, D. S., and Schulze, W. D., editors, *Valuing Environmental Goods: A State of the Arts Assessment of the Contingent Valuation Method*. Rowman & Allenheld, Totowa, NJ.

Ciriacy-Wantrup, S. (1947). Capital returns from soil-conservation practices. *Journal of Farm Economics*, 29:1181–1196.

Diamond, P. A. and Hausman, J. A. (1994). Contingent valuation: Is some number better than no number? *The Journal of Economic Perspectives*, 8(4):45–64.

Hanemann, W. M. (1994). Valuing the environment through contingent valuation. *The Journal of Economic Perspectives*, 8(4):19–43.

Hanley, N., Wright, R. E., and Adamowicz, V. (1998). Using choice experiments to value the environment. *Environmental and Resource Economics*, 11(3-4):413–428.

Hill, R. C., Griffiths, W. E., and Judge, G. G. (2001). *Undergraduate Econometrics Second Edition*. John Wiley & Sons, Hoboken, NJ.

Kagel, J. H. and Roth, A. E., editors (1995). *Handbook of Experimental Economics*. Princeton University Press, Princeton.

Katz, M. L. and Shapiro, C. (1994). Systems competition and network effects. *The Journal of Economic Perspectives*, 8(2):93–115.

Körner, S. and Wahlgren, L. (2000). *Statistisk Dataanalys*. Studentlitteratur, Lund.

Layton, D. and Brown, G. (1998). Application of stated preference methods to a public good: Issues for discussion. Paper presented at the NOAA Workshop on the Application of Stated Preference Methods to Resource Compensation, Washington, DC, June 1-2, 1998.

McCarthy, C. (2008). Myspace to developers: Come play in our sandbox! World Wide Web electronic publication. `http://www.news.com/8301-13577_3-9864571-36.html` [Accessed 10 June 2008].

Mitchell, R. C. and Carson, R. T. (1989). *Using Surveys to Value Public Goods: The Contingent Valuation Method*. Resources for the Future, Washington, DC.

Mosteller, F. and Nogee, P. (1951). An experimental measurement of utility. *The Journal of Political Economy*, 59(5):371–404.

Rousseas, S. W. and Hart, A. G. (1951). Experimental verification of a composite indifference map. *The Journal of Political Economy*, 59(4):288–318.

Ryan, M. and Hughes, J. (1997). Using conjoint analysis to assess women's preferences for miscarriage management. *Health Economics*, 6(3):261–273.

Samples, K. C. and Hollyer, J. R. (1990). Contingent valuation of wildlife resources in the presence of substitutes and complements. In Johnson, R. L. and Johnson, G. V., editors, *Economic Valuation of Natural Resources: Issues, Theory and Applications*, pages 177–192. Westview Press, Boulder.

Shapiro, C. and Varian, H. R. (1998). *Information Rules: A Strategic Guide to the Network Economy*. Harvard Business School Press, Cambridge, MA.

Thurstone, L. L. (1931). The indifference function. *Journal of Social Psychology*, 2:139–167.

Varian, H. R. (2006). *Intermediate Microeconomics: A Modern Approach*. W.W. Norton & Co., London.

von Neumann, J. and Morgenstern, O. (1944). *Theory of Games and Economic Behavior*. Princeton University Press, Princeton.

Wallis, W. A. and Friedman, M. (1942). The empirical derivation of indifference curves. In Lange, O., McIntyre, F., and Yntema, T. O., editors, *Studies in Mathematical Economics and Econometrics in memory of Henry Schultz*. University of Chicago Press, Chicago.

A Choice sets and price matrix

Choice sets; A lists alternatives for Google (Facebook), and B for Microsoft Live (MySpace). Row number m corresponds to question number, and columns n to possible choices for question m.

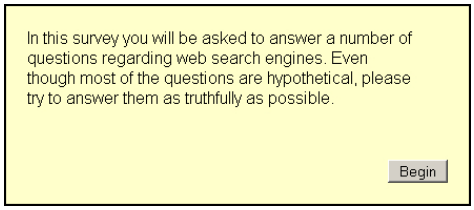
$$A = \begin{pmatrix} 0 & 10 & 20 & 30 & 40 & 50 \\ 0 & 10 & 20 & 30 & 40 & 50 \\ 0 & 10 & 20 & 30 & 40 & 50 \\ 0 & 10 & 20 & 30 & 40 & 50 \\ 0 & 10 & 20 & 30 & 40 & 50 \\ 0 & 9 & 18 & 27 & 36 & 45 \\ 0 & 6 & 13 & 20 & 26 & 33 \\ 0 & 5 & 10 & 15 & 20 & 25 \\ 0 & 2 & 4 & 6 & 8 & 10 \end{pmatrix}$$

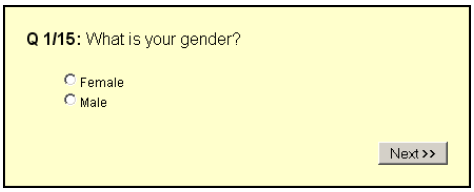
$$B = \begin{pmatrix} 50 & 40 & 30 & 20 & 10 & 0 \\ 45 & 36 & 27 & 18 & 9 & 0 \\ 33 & 26 & 20 & 13 & 6 & 0 \\ 25 & 20 & 15 & 10 & 5 & 0 \\ 10 & 8 & 6 & 4 & 2 & 0 \\ 50 & 40 & 30 & 20 & 10 & 0 \\ 50 & 40 & 30 & 20 & 10 & 0 \\ 50 & 40 & 30 & 20 & 10 & 0 \\ 50 & 40 & 30 & 20 & 10 & 0 \end{pmatrix}$$

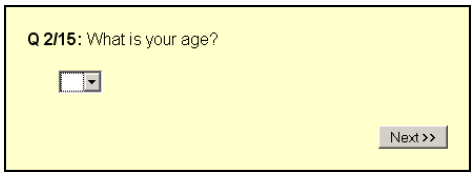
Below is the price matrix regulating the service prices, equal for both questionnaires. Row number m corresponds to the services; number one corresponds to Google (Facebook) and number two to Microsoft Live Search (MySpace).

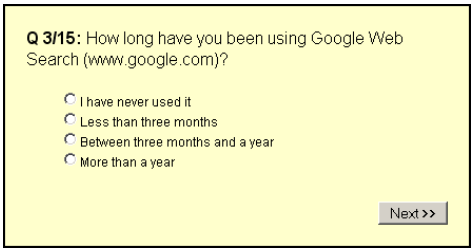
$$P = \begin{pmatrix} 0.10 & 0.11 & 0.15 & 0.20 & 0.50 & 0.10 & 0.10 & 0.10 & 0.10 \\ 0.10 & 0.10 & 0.10 & 0.10 & 0.10 & 0.11 & 0.15 & 0.20 & 0.50 \end{pmatrix}$$

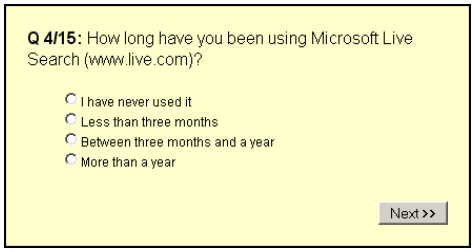
B Questionnaire 1

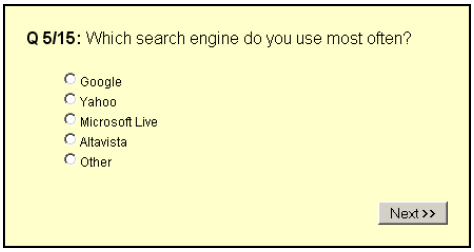


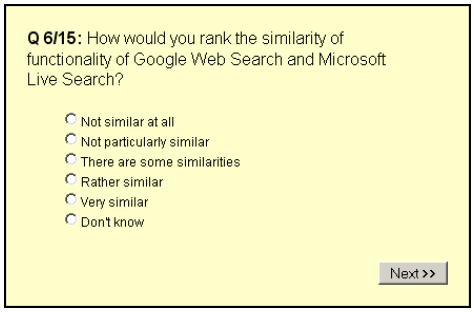


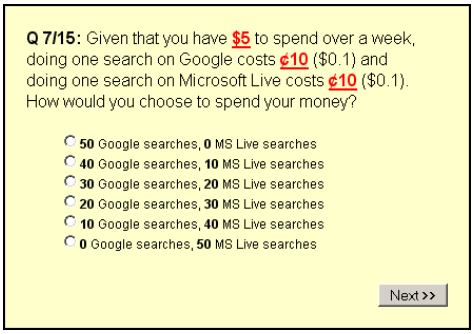












Q 8/15: Given that you have **$5** to spend over a week, doing one search on Google costs **¢11** ($0.11) and doing one search on Microsoft Live costs **¢10** ($0.1). How would you choose to spend your money?

- **45** Google searches, **0** MS Live searches
- **36** Google searches, **10** MS Live searches
- **27** Google searches, **20** MS Live searches
- **18** Google searches, **30** MS Live searches
- **9** Google searches, **40** MS Live searches
- **0** Google searches, **50** MS Live searches

Next >>

Q 9/15: Given that you have **$5** to spend over a week, doing one search on Google costs **¢15** ($0.15) and doing one search on Microsoft Live costs **¢10** ($0.1). How would you choose to spend your money?

- **33** Google searches, **0** MS Live searches
- **26** Google searches, **10** MS Live searches
- **20** Google searches, **20** MS Live searches
- **13** Google searches, **30** MS Live searches
- **6** Google searches, **40** MS Live searches
- **0** Google searches, **50** MS Live searches

Next >>

Q 10/15: Given that you have **$5** to spend over a week, doing one search on Google costs **¢20** ($0.2) and doing one search on Microsoft Live costs **¢10** ($0.1). How would you choose to spend your money?

- **25** Google searches, **0** MS Live searches
- **20** Google searches, **10** MS Live searches
- **15** Google searches, **20** MS Live searches
- **10** Google searches, **30** MS Live searches
- **5** Google searches, **40** MS Live searches
- **0** Google searches, **50** MS Live searches

Next >>

Q 11/15: Given that you have **$5** to spend over a week, doing one search on Google costs **¢50** ($0.5) and doing one search on Microsoft Live costs **¢10** ($0.1). How would you choose to spend your money?

- **10** Google searches, **0** MS Live searches
- **8** Google searches, **10** MS Live searches
- **6** Google searches, **20** MS Live searches
- **4** Google searches, **30** MS Live searches
- **2** Google searches, **40** MS Live searches
- **0** Google searches, **50** MS Live searches

Next >>

Q 12/15: Given that you have **$5** to spend over a week, doing one search on Google costs **¢10** ($0.1) and doing one search on Microsoft Live costs **¢11** ($0.11). How would you choose to spend your money?

- **50** Google searches, **0** MS Live searches
- **40** Google searches, **9** MS Live searches
- **30** Google searches, **18** MS Live searches
- **20** Google searches, **27** MS Live searches
- **10** Google searches, **36** MS Live searches
- **0** Google searches, **45** MS Live searches

Next >>

Q 13/15: Given that you have **$5** to spend over a week, doing one search on Google costs **¢10** ($0.1) and doing one search on Microsoft Live costs **¢15** ($0.15). How would you choose to spend your money?

- **50** Google searches, **0** MS Live searches
- **40** Google searches, **6** MS Live searches
- **30** Google searches, **13** MS Live searches
- **20** Google searches, **20** MS Live searches
- **10** Google searches, **26** MS Live searches
- **0** Google searches, **33** MS Live searches

Next >>

Q 14/15: Given that you have **$5** to spend over a week, doing one search on Google costs **¢10** ($0.1) and doing one search on Microsoft Live costs **¢20** ($0.2). How would you choose to spend your money?

- **50** Google searches, **0** MS Live searches
- **40** Google searches, **5** MS Live searches
- **30** Google searches, **10** MS Live searches
- **20** Google searches, **15** MS Live searches
- **10** Google searches, **20** MS Live searches
- **0** Google searches, **25** MS Live searches

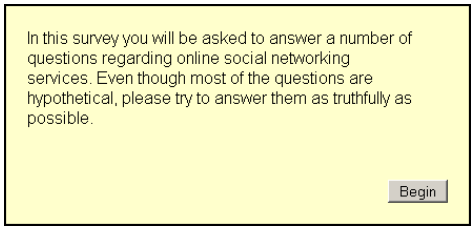
Next >>

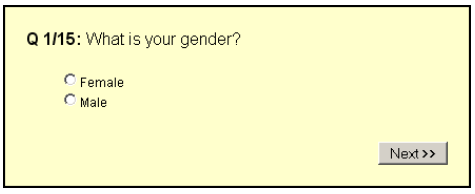
Q 15/15: Given that you have **$5** to spend over a week, doing one search on Google costs **¢10** ($0.1) and doing one search on Microsoft Live costs **¢50** ($0.5). How would you choose to spend your money?

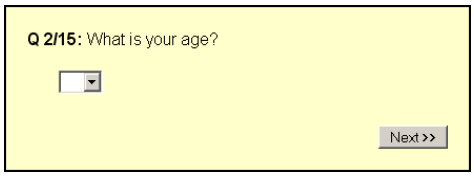
- **50** Google searches, **0** MS Live searches
- **40** Google searches, **2** MS Live searches
- **30** Google searches, **4** MS Live searches
- **20** Google searches, **6** MS Live searches
- **10** Google searches, **8** MS Live searches
- **0** Google searches, **10** MS Live searches

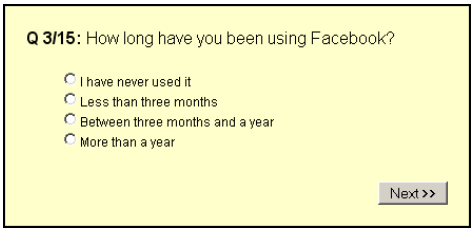
Next >>

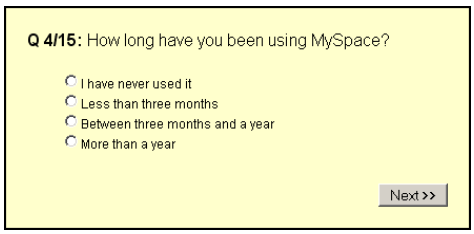
C Questionnaire 2

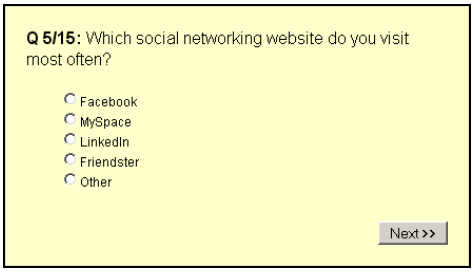


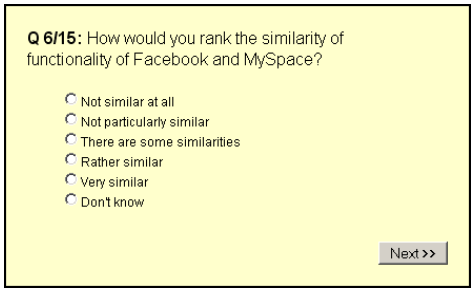












Q 8/15: Given that you have **$5** to spend over a week, visiting Facebook.com costs **¢11** ($0.11) a minute and visiting MySpace.com costs **¢10** ($0.1) a minute. How would you choose to spend your time?

- **45** min on Facebook, **0** min on MySpace
- **36** min on Facebook, **10** min on MySpace
- **27** min on Facebook, **20** min on MySpace
- **18** min on Facebook, **30** min on MySpace
- **9** min on Facebook, **40** min on MySpace
- **0** min on Facebook, **50** min on MySpace

Next >>

Q 9/15: Given that you have **$5** to spend over a week, visiting Facebook.com costs **¢15** ($0.15) a minute and visiting MySpace.com costs **¢10** ($0.1) a minute. How would you choose to spend your time?

- **33** min on Facebook, **0** min on MySpace
- **26** min on Facebook, **10** min on MySpace
- **20** min on Facebook, **20** min on MySpace
- **13** min on Facebook, **30** min on MySpace
- **6** min on Facebook, **40** min on MySpace
- **0** min on Facebook, **50** min on MySpace

Next >>

Q 10/15: Given that you have **$5** to spend over a week, visiting Facebook.com costs **¢20** ($0.2) a minute and visiting MySpace.com costs **¢10** ($0.1) a minute. How would you choose to spend your time?

- **25** min on Facebook, **0** min on MySpace
- **20** min on Facebook, **10** min on MySpace
- **15** min on Facebook, **20** min on MySpace
- **10** min on Facebook, **30** min on MySpace
- **5** min on Facebook, **40** min on MySpace
- **0** min on Facebook, **50** min on MySpace

Next >>

Q 11/15: Given that you have **$5** to spend over a week, visiting Facebook.com costs **¢50** ($0.5) a minute and visiting MySpace.com costs **¢10** ($0.1) a minute. How would you choose to spend your time?

- **10** min on Facebook, **0** min on MySpace
- **8** min on Facebook, **10** min on MySpace
- **6** min on Facebook, **20** min on MySpace
- **4** min on Facebook, **30** min on MySpace
- **2** min on Facebook, **40** min on MySpace
- **0** min on Facebook, **50** min on MySpace

Next >>

Q 12/15: Given that you have **$5** to spend over a week, visiting Facebook.com costs **¢10** ($0.1) a minute and visiting MySpace.com costs **¢11** ($0.11) a minute. How would you choose to spend your time?

- **50** min on Facebook, **0** min on MySpace
- **40** min on Facebook, **9** min on MySpace
- **30** min on Facebook, **18** min on MySpace
- **20** min on Facebook, **27** min on MySpace
- **10** min on Facebook, **36** min on MySpace
- **0** min on Facebook, **45** min on MySpace

Next >>

Q 13/15: Given that you have **$5** to spend over a week, visiting Facebook.com costs **¢10** ($0.1) a minute and visiting MySpace.com costs **¢15** ($0.15) a minute. How would you choose to spend your time?

- **50** min on Facebook, **0** min on MySpace
- **40** min on Facebook, **6** min on MySpace
- **30** min on Facebook, **13** min on MySpace
- **20** min on Facebook, **20** min on MySpace
- **10** min on Facebook, **26** min on MySpace
- **0** min on Facebook, **33** min on MySpace

Next >>

Q 14/15: Given that you have **$5** to spend over a week, visiting Facebook.com costs **¢10** ($0.1) a minute and visiting MySpace.com costs **¢20** ($0.2) a minute. How would you choose to spend your time?

- **50** min on Facebook, **0** min on MySpace
- **40** min on Facebook, **5** min on MySpace
- **30** min on Facebook, **10** min on MySpace
- **20** min on Facebook, **15** min on MySpace
- **10** min on Facebook, **20** min on MySpace
- **0** min on Facebook, **25** min on MySpace

Next >>

Q 15/15: Given that you have **$5** to spend over a week, visiting Facebook.com costs **¢10** ($0.1) a minute and visiting MySpace.com costs **¢50** ($0.5) a minute. How would you choose to spend your time?

- **50** min on Facebook, **0** min on MySpace
- **40** min on Facebook, **2** min on MySpace
- **30** min on Facebook, **4** min on MySpace
- **20** min on Facebook, **6** min on MySpace
- **10** min on Facebook, **8** min on MySpace
- **0** min on Facebook, **10** min on MySpace

Next >>