# Valuing the Internet

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## 1 Motivation

The arrival of the internet has transformed almost all facets of society over the past 20 years. However, traditional measures of GDP have not picked up the enormous gains in consumer welfare that have likely occurred. This disconnect comes in part from the fact that sites such as Facebook absorb large fractions of global leisure time yet are provided for free to consumers. While the ad revenue generated by Facebook and others is accounted for, with consumers in effect paying through their consumption of ads, this approach likely misses the true extent of the welfare gains generated by internet usage. This project aims to provide a reasonable measure of the size of the gains generated by the internet, and potentially shed light on the question of whether the rate of welfare growth has accelerated over time in contrast to GDP growth that has remained fairly stable.

## 2 Existing Literature

There has been much recent discussion on measuring GDP and the potential mismeasurement of internet-induced GDP growth. For example, see Syverson 2017 and Groshen et al. 2017 in the recent Journal of Economic Perspectives symposium "Are Measures of Economic Growth Biased?", as well as Ahmad and Schreyer 2016, and Nakamura et al. 2016. These papers discuss issues related to valuing a good in GDP that is provided for free to consumers, but do not seek to calculate the welfare benefits of the internet and related technologies as traditional GDP measures are concerned with measuring the value of output rather than welfare.

Several papers go further and attempt such a calculation. Hulten and Nakamura 2017 add a consumption technology into a Solow growth model to estimate consumer gains from the internet. Closest to our approach is Goolsbee and Klenow 2006 and Brynjolfsson and Oh 2012 who try to measure the surplus generated by the internet from the time spent using the internet and the value of leisure. As described in the methodology below, leveraging the Nielsen data, we extend this approach both theoretically and empirically to provide more plausible estimates of the welfare gains from the internet.

## 3 Methodology Outline

In order to allow us to discuss the welfare gains due to quality improvements in the Internet, suppose that consumers have a utility function which takes the following form:

$$U\left(\{q_i h_i\}_{i=1}^{N}, \widetilde{Q}\widetilde{H}\right) = \left(\left(\left(\sum_{i=1}^{N}(q_i h_i)^{1/\sigma}\right)^{\sigma}\right)^{1/\mu} + \left(\widetilde{Q}\widetilde{H}\right)^{1/\mu}\right)^{\mu}$$

where $h_i$ are hours spent on a leisure activity $i$ and $q_i$ is the quality of that activity. $\widetilde{H}$ is the total hours spent on non-leisure activities and $\widetilde{Q}$ is their quality, which captures the value of non-leisure hours. The total number of hours spent on leisure is $H$ so that

$$\sum_{i=1}^{N} h_i = H.$$

We also have that

$$H + \widetilde{H} = 1$$

since the total number of hours are fixed in the day and normalized to 1. Therefore, $H$ represents the fraction of leisure hours spent on the leisure.

First order conditions for household optimization imply that the leisure share of activity and the ratio of leisure to non-leisure hours, respectively, satisfy the following equations:

$$\frac{h_i}{H} = \left(\frac{q_i}{Q}\right)^{-1/(1-\sigma)} \quad \text{where } Q = \left(\left(\sum_{i=1}^{N} q_i^{-1/(1-\sigma)}\right)^{-(1-\sigma)}\right)$$

$$\frac{H}{\widetilde{H}} = \left(\frac{Q}{\widetilde{Q}}\right)^{-1/(1-\mu)}$$

and $Q$ is an aggregator of quality for leisure goods.

Suppose that we observe some information on the the change in the quality of good 1. It follows that

$$d\log\frac{h_1}{H} = -\frac{1}{1-\sigma}\frac{H-h_1}{H}d\log q_1.$$

Moreover,

$$d\log\frac{H}{1-H} \quad = \quad -\frac{1}{1-\mu}d\log Q = -\frac{1}{1-\mu}\frac{h_1}{H}d\log q_1$$

where recall that $H$ is the fraction of total leisure time not spent on mobile. Therefore, given a measurable change in the quality of one good together with information on the change in the

time spent on that leisure good relative to other leisure goods, we can determine the values of the elasticities of the utility function. Using these elasticities, we can determine the value of the qualities of different leisure goods from data on hours spent on these goods. Furthermore, using these measures of quality, we can perform counterfactual exercises to determine by how much welfare would have changed under different trajectories for the quality of the Internet.

Of course, this approach requires accurate measures of quality. We are currently pursuing multiple approaches to infer quality changes within activities that draw on observable correlates of quality and use semi- or non-parametric methods to, at the minimum, reveal changes in the growth rate of welfare. Alternatively, if we observe changes in prices of costly leisure goods (e.g. movies, video on demand etc.), and know the value of time as in Goolsbee and Klenow (2006) or estimate it by extending the model above, we can estimate the elasticities of substitution between these activities and internet usage needed to make welfare calculations. We plan on pursuing both approaches.

# 4 Data Requested and Empirical Approach

With the goal of estimating how consumers substitute between internet usage and other leisure activities, as well as the time allocations devoted to each leisure activity (both essential inputs into our welfare calculations), we are requesting access to the following datasets. Should additional funds be needed we anticipate being able to raise money from internal and external sources.

## 4.1 Scarborough Surveys

We would like to know how households allocate their time across different leisure activities (internet usage, pay per view movie, going to cinema, outdoor sports etc.), both in the cross-section (across households in different markets) and over time within the same market. We require that these household surveys are matched to a geographic location (a market is sufficient) since we plan to explore how these time allocations respond to relative price and quality changes in leisure activities obtained from outside data sources.

While household-level identifiers are desirable, we can make progress with identifiers unique to a particular demographic-group and market. We note that although a preliminary analysis is possible using the American Time Use Survey, the broadness of the categories in that survey make our proposed analysis impossible since the match to prices for such broad activities is a heroic task. In contrast, the Scarborough surveys have detailed information on subscriptions paid for various leisure activities (VOD, cable subscription, etc.), as well as information on the type of activity (e.g. take out Mexican food), that makes matching activities to relative prices and qualities feasible.

We would ultimately like to use the Scarborough Surveys to create a panel at as disaggregated level as possible of participation in various leisure activities and leisure services purchased using the digital/internet, lifestyle, media, restaurant and sports sections of the Scarborough Surveys.[1]

[1] Section based on the What's in Guide here http://en-us.nielsen.com/sitelets/cls/documents/scarborough/Scarborough-Whats-In-Guide-2016.pdf.

### 4.2 Computer Browsing and Mobile Browsing and App Usage

Although less essential than the Scarborough dataset above, it would be valuable to decompose the welfare gains from the internet by various types of internet usage. For this exercise, we would like to know how consumers allocate their time between various internet-based activities, on both phones and computers. We believe this information is contained in the Digital Content Ratings dataset. We would ideally like data at the demographic-group market level as above, at as high frequency as possible. We hope to exploit shocks to the quality of non-internet leisure activities (unusual weather, big sports game etc.), so having daily data would be ideal. Hence we would like data at the demographic-group-by-market-by-day level if possible.

### 4.3 Aggregate Television Time Use Data from Nielsen's Advanced TV Ratings

If possible, a third dataset would be useful. This would be time spent watching television at the same level of granularity as the computer and mobile browsing data above (demographic-group-by-market-by-day). We do not require information on particular television programs watched. These data will be used to look at substitution between television and internet and we hope to be able to match these data to either shocks in relative prices, or shocks in relative quality (e.g. when there is a particularly big television event, how does internet use respond).

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