Smart Pricing Grows the Pie

Guy Calvert

guy.calvert@gmail.com

Abstract. Some publisher advertising networks provide features intended to help advertisers bid more efficiently with a single bid in many publishers' click auctions at once – Smart Pricing on the Google Display Network is one example. Typically such features involve discounting advertiser bids or prices for clicks on publisher websites according to how click values vary across sites (for some appropriate measure of advertiser value). Contrary to concerns that such features necessarily result in reduced publisher (and network) revenue we find that, in many simple cases, the modified auction dynamics produce rational incentives for advertisers to bid more – and spend more – than they would without the benefit of these features. So if advertisers act in their own interest then publishers and networks stand to make more revenue as well.

1 Introduction

Internet website advertising is big business these days, accounting for billions of dollars of advertising budgets each year. It works like this: whenever an internet user opens or refreshes a publisher's web page, advertisements are displayed on publisher-specified locations on that page (ad slots). Depending on prior arrangement with the publisher, advertisers are typically billed for this in one of three ways:

1. A direct price for having the ad displayed (cost per thousand impressions, CPM), or
2. A contingent price, paid if and only if a user clicks on the ad (cost per click, CPC), or
3. A contingent price, paid if and only if the user performs some other advertiser-desired action (cost per action, CPA).

The important details of this process pertain to how publishers price their ad slots to extract maximum ad revenue, and – given that pricing – how businesses should bid for each publisher's ad slots so as to maximize profits from their advertising investment. Large-budget advertisers may negotiate directly with publishers for some or all of their inventory, with the terms being settled between the advertiser and the publisher's direct sales team. Alternatively, publishers may wish to save these transaction costs with respect to a portion of their inventory.

One solution offered up by the internet advertising marketplace is the *publisher network* - examples include the Google Display Network (GDN), the Yahoo Publisher Network (YPN), AOL's Advertising.com, Microsoft's growing ad network, Quigo's content network, and many others. Publishers sign up with one or more networks, which then shop their entire portfolio of publisher inventory to advertisers, and the resulting network-sourced advertising revenue on each publisher is split between the network and the publisher (an arrangement commonly known as *revenue sharing*). Each network publisher's inventory is typically assigned and priced in real time according to a network-administered auction that is triggered each time a user views/refreshes the publisher's webpage. Advertisers may specify some targeting criteria (e.g. keywords, user demographics, and so forth), along with a single bid with which they will contest all of the auctions associated with the inventory they targeted within the network. On both Google and Yahoo! CPC bidding advertisers bid according to the maximum CPC they are prepared to pay for clicks they receive anywhere in the network, and are ranked according to some function of this bid and their *ad quality score*, a measure of (among other things) how the ad is expected to perform[1] on the given web page. With this *one-bid-for-many-auctions* mechanism, networks allow businesses to advertise on many publisher websites - big and small – with relatively little fuss.

The main benefit of one-bid-for-many-auctions is that it does away with the need for ads to bid separately on each individual publisher's inventory. But the flip side of this benefit is that – leaving aside transaction costs – advertisers are not bidding as profitably as possible, since network bidding is by its nature less profitable on a per-site basis than separate bidding. This is because clicks on different websites convert to actions (sales, subscriptions, leads, etc, whatever the advertiser was ultimately hoping to achieve) at disparate rates, so click values vary across the network. Moreover the competition for those clicks may also differ from website to website for a variety of reasons. Consequently an advertiser's profit-maximizing network bid will in general be quite different from its profit-maximizing bid for any one participating publisher's website. For example, as we discuss below, if the network configures its auctions such that the profit-maximizing strategy is for advertisers to bid their value for the clicks in each auction, then the advertiser's profit-maximizing network bid will be a weighted average of its click-values from inventory across the network. So advertisers end up bidding too much – and ultimately paying too much – for low-value clicks, and too little for high-value clicks. The concern is that this creates something analogous to a “lemons market” dynamic[2] in which publishers who produce high-value clicks effectively subsidize publishers who produce low-value clicks. The perverse consequence of this is that publishers which produce low-value clicks flourish at the expense of publishers which produce high-value clicks, who would in turn gradually drop out of the network. This would act to reduce the appeal of the network to advertisers (who may then choose to opt out of the network altogether) and in any case depresses network revenue. So it’s in everyone's interests – advertisers, publishers, and the network itself – to help advertisers use network bidding more efficiently.

Networks sometimes address this issue by overlaying their auction processes with proprietary pricing tools. Google led the way with the introduction of "Smart Pricing" on the GDN in 2004 (1) and Yahoo followed in 2007 with the rollout of "Quality-Based Pricing" on the YPN. The details presumably vary from network to network, but at heart is the principle that advertisers should ultimately pay less for low-value clicks than for high-value clicks. There has already been some academic work focused on the impact of such pricing tools on network revenues. Stanford researchers Mungamuru and Garcia-Molina developed a whole-ecosystem model suggesting that networks who adopt these pricing tools (which they label *predictive pricing* programs) stand to

[1] Ad quality is typically some function of the probability the ad will get clicked (the “click-through-rate”, or CTR), along with other factors of concern to publishers, but is generally independent of the advertiser’s max CPC bid.
[2] In the classic exposition, lemons markets occur when buyers are unable to distinguish high-quality goods (“cherries”) from low-quality goods (“lemons”). So buyers bid according to the average value of goods in the market, which is attractive to lemons sellers but too low for sellers of cherries. Consequently, everyone selling cherries withdraws from the market, leaving behind a market for lemons only (4).

make more money than networks that eschew such programs (2). The way their models shake out, predictive pricing confers a competitive advantage that enables the adopting network to attract both more advertiser spending and more publisher traffic. The implication is that networks that adopt predictive pricing tools prosper at the expense of those that do not.

Still, the question remains of whether predictive pricing tools have the potential to do any more than stem losses by defraying network opt-out and defection to competitors. Since such tools involve somehow or other discounting the price each advertiser pays for clicks, publishers sometimes complain that their revenue can only suffer as a result. Indeed publisher reaction to Smart Pricing, for example, ranges from understanding to skepticism to outright hostility (3).

But as we shall discuss, bidding efficiency features like Google's Smart Pricing[4] produce rational incentives for advertisers to raise their bids. The question is whether – by comparison with the State of Nature – Smart Pricing induced bid increases result in increased revenue to the network (and so, on average, to publishers[5]). The main objective of this note is to illustrate that such an outcome is not only possible but also quite natural, following from the simplest assumptions regarding network auction structure and advertiser objectives. In our model, Smart Pricing results in incremental gains to advertisers, publishers, and the network, and in contrast to (2) these gains come purely as a result of reducing the inefficiency that derives from one-bid-for-many-auctions, and not at all due to publishers or advertisers shifting business from one network to another – indeed it is irrelevant in our model how other networks behave. In other words, Smart Pricing can grow the pie, for publishers and networks alike.

2 Impact of Smart Pricing on Advertiser Profitability

As discussed above, we suppose that each advertiser a specifies the maximum CPC m_a that it is prepared to pay for clicks it wins in the network auctions it contests. Suppose also that on any publisher[6] p the network applies a Smart Pricing model to modify each advertiser's max CPC bid, multiplying it by a discount factor[7] $k_{a,p} \leq 1$. This *adjusted* max CPC bid $k_{a,p}m_a$ is used along with other criteria to determine the ad's rank in each publisher auction. In the next section we will consider specific auction structures along these lines, but first it is worth noting the

[4] The authors of (2) suggest a mechanism whereby networks discount advertisers' auction-determined click prices according to some predictive pricing factor associated with the publisher whose traffic produced the clicks. Note though that not all predictive pricing tools work in this way. The essence of Google's Smart Pricing, at least, is that it modifies advertiser pre-auction bids, rather than modifying their post-auction prices, although the resulting effect is similar – advertisers pay less for lower quality clicks than for higher quality clicks. Here we confine our attention to the study of such bid-modification systems, which for simplicity we collectively refer to as "Smart Pricing" rather than "features like Smart Pricing".

[5] That an increase to network revenue implies an increase to average per-publisher revenue follows if we assume the network splits all advertising revenue in the same proportion with every publisher. This is for example the case with AdSense Online publishers participating in the GDN. (5)

[6] For economy of notation we assume without loss of generality that each publisher contributes exactly one web page to the network, even though in reality a single publisher may host network ad slots on several web pages.

[7] The bid modifier is generally assumed to be smaller than 1, so that the ad's adjusted max CPC bid for each publisher auction is everywhere smaller than its prescribed network max CPC bid m_a.

impact of Smart Pricing bid modifiers within a more general framework. For this we make only the following two assumptions regarding the auction:

1. On any individual publisher p, it would never be profit-maximizing for an advertiser to bid a max CPC that is higher than its value for clicks from that publisher
2. On any publisher p, the advertiser's auction-determined click price $t_{a,p}$ is always lower than its adjusted max CPC $k_{a,p}m_a$

Denote by $u_{a,p}$ the advertiser's value for clicks produced on publisher p. If the advertiser values its desired post-click action at v_a (which we will assume for simplicity is independent of the publisher[8]) and we write $\pi_{a,p}$ for the probability of an action conditional on a click (or *conversion rate*), then clearly:

$$u_{a,p} = v_a \pi_{a,p}$$

Suppose the advertiser can win profitable clicks somewhere on the network, i.e. there is some non-empty subset of network publisher web pages where, if the advertiser were bidding separately for this inventory, it could in each case find a profitable winning bid that wins a positive number of clicks. Write g_a for the publisher within this subset which produces maximally valued clicks for a, and let $\widetilde{m}_a$ be the profit-maximizing bid on g_a. Define the bid modifiers as:

$$k_{a,p} = \min\left(\frac{u_{a,p}}{u_{a,g_a}}, 1\right) = \min\left(\frac{\pi_{a,p}}{\pi_{a,g_a}}, 1\right)$$

In this case, if the advertiser adopts $\widetilde{m}_a$ as its network bid, then its profit-per-click on any publisher p where it wins clicks is just:

$$P_{a,p} = (u_{a,p} - t_{a,p}) \geq (u_{a,p} - k_{a,p}\widetilde{m}_a) \geq \left(u_{a,p} - \frac{\pi_{a,p}}{\pi_{a,g_a}}\widetilde{m}_a\right) = (u_{a,g} - \widetilde{m}_a)\frac{\pi_{a,p}}{\pi_{a,g_a}} > 0$$

It follows that with these bid modifiers the advertiser can find a network bid which is nowhere-unprofitable and is positively profitable at least in some places on the network. And in certain special cases (such as our simplified auction model below) these bid modifiers enable advertisers to find a bid that optimizes their profitability, in the sense of matching the profitability attainable via separate bidding. In general this is not so, but in any case such bid modifiers should at least defray advertiser concerns about losing money on the network.

[8] This is a pretty fair assumption for actions that align with online sales, but the value of other types of actions (such as registrations for lead generation purposes), may well vary across publishers due to demographic/other characteristics of the publisher's traffic. Consider for example a mortgage-financer with a campaign to drive registrations for lead generation purposes - leads sourced from a publisher with a low-income audience are worth less than leads sourced from publishers with high-income audiences.

3 Simplified Auction Model

In this section we consider a more specific auction structure applied within a special network scenario, with the intent of demonstrating that Smart Pricing has the potential to increase network revenue.

For advertiser a and publisher p, we suppose the auction ranking function (ARF) is of the form $b_{a,p} = k_{a,p} m_a Q_{a,p}$, where $Q_{a,p}$ is the advertiser's quality score on this publisher – this is generally some function of $\gamma_{a,p}$, the advertiser's expected click-through-rate (or CTR, the probability of a click conditional on an impression) on the publisher, but may also depend on other factors. For the purposes of our demonstration we suppose also that:

A. Each publisher web page offers up exactly one ad slot for network auctions.
B. All advertisers contest all publisher ad slots across the network (i.e. there's no targeting).
C. The network allocates the ad slot on each page according to a second-place auction – ads are ranked highest-to-lowest according to the ARF, and the highest ranked ad wins the slot and pays the minimum adjusted max CPC that could have been bid to retain the winning position.

In other words, if we write σ_p for the ordering of ads on p as determined by the ARF so that:

$$b_{\sigma_p(1),p} \geq b_{\sigma_p(2),p} \geq \cdots$$

Then the winning ad $\sigma_p(1)$ will pay a CPC given by:

$$c_p = \frac{k_{\sigma_p(2),p} m_{\sigma_p(2)} Q_{\sigma_p(2),p}}{Q_{\sigma_p(1),p}}$$

We can now derive each advertiser's profit-maximizing network bid $\widehat{m}_a$ (given a particular choice of bid modifiers $k_{a,p}$), and deduce from that an expression for total seller revenue from all network auctions. Suppose the publisher produces n_p page views in a given period, and denote by $E_{a,p}$ the expected profit of the advertiser on a given publisher. If we define $x_{a,p} \equiv n_p \gamma_{a,p}$ as the expected number of clicks on p that could be won by a (if she prevails in the auction), and $f_{-a,p}$ for a's probability distribution function of the highest ARF on p from all ads but a (this represents a's beliefs regarding market price levels on p), then we have:

$$E_{a,p} = \int_0^{b_{a,p}} f_{-a,p}(y) x_{a,p} \left(u_{a,p} - \frac{y}{Q_{a,p}} \right) dy$$

Differentiating this by m_a and setting the result to zero, we see that the advertiser's profit on a particular publisher is maximized so long as $u_{a,p} - k_{a,p} m_a = 0$, i.e. if the adjusted max CPC bid is set to the click-value. However if the advertiser a is bidding across the entire network then the expected profit $E[P_a]$ given max CPC bid m_a is given by[9]:

$$E[P_a] = \sum_p E_{a,p} = \sum_p \int_0^{b_{a,p}} f_{-a,p}(y) x_{a,p} \left(u_{a,p} - \frac{y}{Q_{a,p}} \right) dy$$

So the ad's profit-maximizing max CPC bid $\widehat{m}_a$ is determined by:

$$(1) \quad 0 = \frac{dE}{dm} = \sum_p k_{a,p} Q_{a,p} \frac{dE_{a,p}}{db_{a,p}} = \sum_p k_{a,p} Q_{a,p} f_{-a,p}(\hat{b}_{a,p}) x_{a,p} (u_{a,p} - k_{a,p} \widehat{m}_a)$$

Here $\hat{b}_{a,p} = k_{a,p} \widehat{m}_a Q_{a,p}$ is the advertiser's profit-maximizing ARF. The above equation can be rearranged to give the advertiser's profit-maximizing max CPC bid as a weighted average of the ratios of the ad's per-publisher click value to its per-publisher bid modifiers:

$$(2) \quad \widehat{m}_a = \frac{\sum_p f_{-a,p}(\hat{b}_{a,p}) x_{a,p} u_{a,p} k_{a,p} Q_{a,p}}{\sum_p f_{-a,p}(\hat{b}_{a,p}) x_{a,p} k_{a,p}{}^2 Q_{a,p}} = \sum_p w_{a,p} \frac{u_{a,p}}{k_{a,p}}$$

The weights $w_{a,p}$ (summing to 1) and are defined by:

$$w_{a,p} = \frac{f_{-a,p}(\hat{b}_{a,p}) x_{a,p} k_{a,p}{}^2 Q_{a,p}}{\sum_q f_{-a,q}(\hat{b}_{a,q}) x_{a,q} k_{a,q}{}^2 Q_{a,q}}$$

So if all advertisers' find their profit-maximizing network bid, the network's overall revenue is:

$$(3) \quad R = \sum_p x_{\sigma_p(1),p} c_p = \sum_p \frac{x_{\sigma_p(1),p} k_{\sigma_p(2),p} \widehat{m}_{\sigma_p(2)} Q_{\sigma_p(2),p}}{Q_{\sigma_p(1),p}}$$

4 Efficient Bidding

We saw above that an advertiser bidding separately on any one publisher would do best to simply bid their click-value $u_{a,p}$. It follows that bid modifiers $k_{a,p}$ that maximize advertiser profit across the network must satisfy:

$$(4) \quad u_{a,p} - k_{a,p} \widehat{m}_a = 0, \quad \forall p$$

[9] Here we assume that the ad handicaps network page views (and therefore clicks) independently of all other parameters.

Networks can enable this by defining:

$$k_{a,p} = \pi_{a,p}/M_a$$

Here M_a is an upper bound to the set of conversion rates $\Pi_a = \{\pi_{a,*}\}$, so that $k_{a,p} \leq 1$. As in the more general case discussed above we will use the least upper bound, setting $M_a = \pi_{a,g}$, where $g = \mathrm{argmax}_p\, \pi_{a,p}$ is the baseline publisher that produces maximal conversion rate for a. So:

$$(5)\quad k_{a,p} \equiv k_{a,p}^{\infty} = \pi_{a,p}/\pi_{a,g}$$

We will refer to this choice of Smart Pricing bid modifiers as *Exact Smart Pricing* (or SP^{∞}). Substituting (5) into (2), it turns out that the advertiser's profit-maximizing strategy under SP^{∞} is to set their network max CPC bid to their maximal per-publisher click-value:

$$(6)\quad \widehat{m}_a = \widehat{m}_a^{\infty} = v_a \pi_{a,g} = u_{a,g}$$

In this case, the advertiser's ARF becomes:

$$(7)\quad \hat{b}_{a,p} \equiv \hat{b}_{a,p}^{\infty} = u_{a,p} Q_{a,p}$$

So with SP^{∞} networks enable advertiser's to close the one-bid-for-many-auctions profitability gap and achieve the same profitability as if they were bidding separately.

5 Network Revenue Impact of Exact Smart Pricing

We derived the network revenue equation (3) above under assumptions A-C regarding the auction configuration. Here we examine the differential impact to network revenue of SP^{∞} versus the State of Nature (in which all bid modifiers are 1), in the basic scenario where the quality score is a function of CTR alone, and all advertisers have the same CTR, that is to say:

1. Each advertiser's quality score $Q_{a,p}$ is a function only of its expected click-through-rate $\gamma_{a,p}$ on the given publisher, and
2. On any given publisher, all advertisers are expected to get the same number of clicks per impression

With these assumptions, we can write:

$$(8)\quad \gamma_{a,p} = \gamma_p, \qquad x_{a,p} = x_p, \qquad Q_{a,p} = Q\left(\gamma_p\right) \equiv Q_p, \qquad \forall a,p$$

According to equation (7) the ARF under SP^{∞} is then just:

$$\hat{b}_{a,p}^{\infty} = u_{a,p} Q_p$$

This implies that under SP^{∞} the ARF ordering σ_p of advertisers on each publisher is just the ordering of advertiser click values. Substituting equations (5-7) into the revenue expression (3) we see that total network revenue under SP^{∞} is given by the click-weighted sum of second-highest click-values:

$$(9) \quad R^{\infty} = \sum_p x_p u_{\sigma_p(2),p}$$

Now consider the situation in the State of Nature (SON). Writing $\hat{m}_a^0$ for an ad's optimal bid in these circumstances, the ARF is now given by:

$$\hat{b}_{a,p}^0 = \hat{m}_a^0 Q_p$$

This implies that under SON the ARF ordering τ_p of advertisers on each publisher p is just the ordering of advertiser bid values, and since that ordering is the same on every publisher we can write $\tau_p = \tau$. It follows also that the probability that the highest competing ARF on publisher p is less than $\hat{b}_{a,p}^0$ is the same as the probability that the highest competing ARF on publisher q is less than $\hat{b}_{a,q}^0$, which implies that the marginal probability $f_{-a,p}(\hat{b}_{a,p}^0)$ is actually independent of p (assuming all advertisers factor this observation into their beliefs). So according to equation (2) an advertiser's optimal network max CPC bid under SON is a weighted average of its click-values across network properties:

$$(10) \quad \hat{m}_a^0 = \frac{\sum_p f_{-a,p}\left(\hat{b}_{a,p}^0\right) x_p Q_p u_{a,p}}{\sum_p f_{-a,p}\left(\hat{b}_{a,p}^0\right) x_p Q_p} = \frac{\sum_p x_p Q_p u_{a,p}}{\sum_p x_p Q_p} = \sum_p w_p u_{a,p}, \qquad w_p = \frac{x_p Q_p}{\sum_q x_q Q_q}$$

Therefore, substituting into (3), the total network revenue under SON is given by the product of total network clicks with the second-highest max CPC bid:

$$(11) \quad R^0 = \hat{m}_{\tau(2)}^0 \sum_p x_p$$

So $R^{\infty} > R^0$ if and only if:

$$(12) \quad \frac{\sum_p x_p u_{\sigma_p(2),p}}{\sum_p x_p} > \hat{m}_{\tau(2)}^0 = \underset{a}{\mathrm{2nd}} \left\{ \sum_p w_p u_{a,p} \right\}$$

In other words, the comparison between the network revenue expressions in the two cases boils down to a comparison between on the one hand a weighted average (across publishers in the network) of second-highest advertiser click-values, and on the other hand, the second-highest advertiser's weighted average of click-values.

The first thing to note is that the condition (12) does not universally hold. For example if there were precisely two advertisers, and we set the quality score to 1, then (12) would be tantamount to the always-false inequality:

$$\sum_p x_p \min_a u_{a,p} > \min_a \left\{ \sum_p x_p u_{a,p} \right\}$$

But with that caveat aside, if there are sufficiently many advertisers and we make reasonable assumptions regarding the functional form of Q and the distributional properties of the other parameters, the condition (12) will very often be satisfied. To see this we can use equations (9) and (11) to estimate to expected revenue ratio $E[R^\infty/R^0]$ by simulation. For our simulations we suppose we have 25 publishers, and that for each a, p the parameters n_p, $u_{a,p}$ and γ_p are independently drawn from uniform distributions on the unit interval [0,1]. We do this for each of four parametric choices of the quality score function $Q_{a,p} = \gamma_{a,p}{}^\alpha$ (setting α in each case to 0, 1, 2, and 3 respectively[10]) and eight choices of the advertiser population N (2, 3, 4, 5, 10, 20, 50, and 100). With 1000 trials in each case, we compute the (geometric) means of the revenue ratios R^∞/R^0 and record the results in Table 1 below:

Table 1: Geometric mean of R^∞/R^0 over 1000 trials, various cases

	$\boldsymbol{\alpha = 0}$	**1**	**2**	**3**
$\boldsymbol{N = 2}$	0.73	0.74	0.76	0.77
3	1.00	1.00	1.01	1.01
4	1.15	1.14	1.13	1.13
5	1.24	1.23	1.22	1.21
10	1.42	1.39	1.36	1.34
20	1.49	1.45	1.42	1.39
50	1.50	1.45	1.41	1.38
100	1.48	1.43	1.39	1.35

So at least with these distributional choices of the parameters, Exact Smart Pricing produces significantly more revenue than the State of Nature even with as few as 4 advertisers (about 13-15%, depending on the functional form of the quality score), and the increase is considerably larger (35-48%) as the number of advertisers grows large. Once there are 4 or more advertisers, SP^∞ outperforms the State of Nature by a greater margin for CPC auctions (in which $\alpha = 0$) than for economic auctions (in which $\alpha = 1$), and the outperformance continues to shrink with α.

[10] For intuition, the $\alpha = 0$ case corresponds to an auction structure in which ads are ranked according to their max CPC bid alone (even if CTR and other factors vary between advertisers), whereas the $\alpha = 1$ case corresponds to an auction structure in which ads are ranked according to the expected CPM they will produce for the publisher (*economic auctions*).

6 Conclusion

The results in Table 1 are of course hostage to the many simplifying assumptions made along the way in order to enable simulations. In practice different advertisers will exhibit different CTRs on any given publisher; the various parameters (page views, CTRs, conversion rates, conversion values) are distributed neither uniformly nor independently (e.g. on any given publisher an advertiser's conversion rate $\pi_{a,p}$, and therefore its click-value $u_{a,p}$, may well be correlated with its click-through rate $\gamma_{a,p}$); the auction ranking process may in any case be more complicated than can be described by the parameterized quality score function in our model; there will typically be more than one ad slot on each publisher page for the auction to assign; networks usually apply targeting approaches which result in each publisher's inventory being contested by a (possibly unique) subset of network advertisers; advertisers may not continuously adjust their bids to their rationally optimal level; and so on. All of these simplifying assumptions naturally bring with them some perturbation to the expected value of R^{∞}/R^{0}, and perhaps in some cases the result is reversed and SP^{∞} underperforms the SON from a revenue perspective. Even the application of SP^{∞} itself will typically stray from the ideal – in practice the (relative) conversion rates at the heart of the SP^{∞} bid modifiers need to be estimated by the network, and each such estimation will have some degree of noise which can dilute the advantage of SP^{∞}. And of course any assessment of the actual revenue impact of Smart Pricing within a given network is necessarily an empirical matter.

What is clear though is that, so long as circumstances at least resemble those laid out in our model, Smart Pricing has the potential to grow the revenue pie for networks and publishers alike, simply by helping advertisers bid more efficiently for each piece of inventory in the network.

References

1. **Google.** About Smart Pricing. *Google AdSense Help Center.* [Online] http://support.google.com/adsense//bin/answer.py?hl=en&answer=190436&sourceid=aso&medium=link&subid=ww-en-et-asblog_2010-09-30.

2. *Predictive Pricing and Revenue Sharing.* **Mungamuru, B. and Garcia-Molina, H.** July 2008, Stanford Infolab Technical Report.

3. **Various forum contributors.** Home / Forums Index / The Google World / Google AdSense / SmartPricing. Why? *WebmasterWorld.com.* [Online] June 3, 2009. http://www.webmasterworld.com/google_adsense/3925664.htm.

4. *The Market for Lemons: Quality Uncertainty and the Market Mechanism.* **Akerlof, George A.** 3, s.l. : MIT Press, August 1970, The Quarterly Journal of Economics, Vol. 84, pp. 488-500.

5. **Google.** The AdSense revenue share. *Google AdSense Blog: Inside AdSense.* [Online] May 24, 2010. http://adsense.blogspot.com/2010/05/adsense-revenue-share.html?utm_source=feedburner&utm_medium=feed&utm_campaign=Feed:+blogspot/tuAm+(Inside+AdSense).