Your call: eBay and demand for the iPhone 4

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Your call: eBay and demand for the iPhone 4

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Abstract

The iPhone 4 was introduced into the UK market on 24th June 2010 to significant consumer interest. This clearly exceeded supply through conventional channels, since there was very extensive activity in terms of bidding on eBay auctions for the product. We monitored all eBay transactions on the iPhone 4 for six weeks from introduction, with total transactions amounting to around £1.5m. We analyse determinants of the winning bid in terms of characteristics of the phone, the seller and the buyer. Our most notable and novel finding relative to previous studies is a very significant premium over list price being paid in almost all cases, with positive uplift factors including whether the phone was unlocked and whether it could be sold overseas. Demand fell over time, as evidenced by lower achieved prices, but the fall in price was relatively modest. A significant premium of 32GB over 16GB versions is revealed.

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1. Introduction

As eBay has grown in the 21st century into an internationally recognized forum for consumer-to-consumer sales (as well as business-to-consumer sales), academic researchers have made extensive use of the information available through its auctions in order to examine various hypotheses, both on specific predictions from auction theory and on matters such as reputation.[1] Our paper focuses on a lesser-examined but possibly more important issue, revelation of information on consumer valuations for an object and the business implications of that information. The chosen object is Apple's iPhone 4 at the time of its introduction into the UK market. We investigate determinants of the magnitude of the winning bid on eBay, the leading e-commerce site in the UK.[2]

The extent of eBay activity on this product is extraordinary. On conservative assumptions, over £1.5 million pounds worth of business was transacted on the iPhone 4 on *ebay.co.uk* over our period of observation, from 24th June 2010, the day it was available in the UK, to 7th August. It is important to recall that Apple had created considerable prior consumer interest and anticipation regarding the product, which had been available in the USA since 7th June.[3] Demand was heightened by the iPhone 3GS (the immediately previous model) being discontinued in the versions most closely substitutable for the iPhone 4 on exactly the same day. As a consequence of the interest, Apple took significant pre-orders and both it and its resellers (principally the mobile phone companies O2, Vodafone and Orange at this stage) experienced continuing shortages until at least mid-August 2010. In total, we recorded almost 30,000 bids across over 2,500 auctions for one or other version of the iPhone 4 within our data sampling period.

Our key finding is quite remarkable. The vast majority of the winning bids were substantially in excess of the list price for the phone, revealing consumer willingness to pay (amongst a self-selected

[1] For an early but authoritative survey, see Bajari and Hortacsu (2004).
[2] According to Nielsen, quoted in Cabral and Hortacsu (2010).
[3] As an example of the hype, consider Apple's slogan for the iPhone 4 "This changes everything. Again."

group of consumers) up to at least double the list price. To our knowledge, this finding is not reported elsewhere in the eBay or similar auction literature.[4]

Table 1 lists key information coming from the auctions we work with. To draw out some highlights, we use 1256 completed sales of the 16GB version, which has a list retail price at the Apple store of £499. Of these sales, the maximum achieved value was £1180 and 1235 sales, that is 98% of them, completed at a value in excess of the list price. The average price was £640.35. The figures for the 32GB version are similarly remarkable. We use 927 completed cases, with a maximum achieved auction value of £1551 and an average price of £778.73 for a product with a list price of £599, 97% of the auctions ending above the list price.

The plan of the paper is as follows. In section 2, we have a brief literature survey, drawing out issues for analysis. Section 3 covers the data, section 4 the model, section 5 the results and the paper concludes with some brief interpretations.

2. Lessons from the literature

A detailed description of the eBay auction process is available in Lucking- Reiley et al. (2007). As Roth and Ockenfels (2002) have pointed out, although eBay auctions have many of the features of second price Vickrey-style auctions, the “hard close” feature leads to a good deal of bidding activity (and “sniping”, specifically) taking place in the closing minutes of the auction- this may have an impact on the extent of demand revelation, as discussed below. Amongst the institutional features that have been found by some researchers to matter to the final achieved price are that minimum bids and reserve prices (where known) can have an influence, that longer auctions have a positive effect and that seller reputation has an impact (see e.g. Lucking- Reiley et al., 2007).

[4] This is not to say the finding is unique. A previous example on a much smaller dataset concerning a fashionable shoehorn is reported briefly in a mimeo note by Waterson and Coombes (2010), available from the corresponding author.

Seller reputation in particular has been examined in a number of papers in the form of an analysis of the relationship between seller price and seller feedback, measured in various ways (e.g. Meinik and Alm, 2002; Houser and Wooders, 2005; Jin and Kato, 2006; also the extensive survey in Bajari and Hortacsu, 2004). Interesting recent examples of analyses of reputation on eBay include Resnick et al.'s (2006) controlled field experiment and Cabral and Hortacsu's (2010) study on the dynamics of reputation. The broad conclusion of these studies is that there is an asymmetry between positive and negative feedback. Additional positive feedback has a markedly lower impact on achieved price (or in Cabral and Hortacsu's case, on sales) than even a small amount of negative feedback.

We turn now to the question of demand revelation in an eBay auction. It is commonly argued that a Vickrey auction, that is a second-price sealed bid auction, leads in principle to accurate revelation of willingness to pay (e.g. Hoffman et al., 1993). At the same time, there may be practical difficulties in administering such an auction in a way that elicits true valuations (Wertenbroch and Skiera, 2002). This is at least equally true of data from eBay auctions, which may either overestimate or underestimate willingness to pay. It is clear that at the lower end of the distribution of willingness to pay, eBay is likely to overestimate consumer valuations, because consumers with valuations lower than the current bid will not enter bids (Barrot et al., 2010). Further, it has been argued (e.g. Zeithammer and Adams, 2010) that eBay does not yield accurate estimates of true willingness to pay because some bidders are "reactive" – rather than using a proxy bid that is capable of revealing their true willingness to pay, they bid a little above the previous bid, but below their valuation. It is this phenomenon that may give rise to the extensive activity observed in the closing stages.

When we consider the winning bid, and not the losing bids, only the second of these issues arises.[5] Thus, the winning bid will not be an overestimate of that bidder's true willingness to pay, but may be an underestimate[6], to the extent that the key bidders are reactive rather than "incremental" (Zeithammer and Adams, 2010). This is of particular interest in cases like ours where the product is

[5] See also Anwar et al. (2006) for complications relating to the winning bid implied by cross-bidding.
[6] This is even after accounting for the fact that the winning bid is the second highest valuation, not the highest.

not freely available at a list price. If it were freely available, there would be no reason for those customers with valuations above list price to reveal these. In our case, we can be assured that, for whatever reason, those who bid, won and paid above the list price, had valuations at least equal to that amount.[7]

Subject to these caveats, identification is based upon the following observation. At the time when the retail outlet is out of stock of the item, and its reappearance is unclear, supply to individual consumers moves from being perfectly elastic at list price (so that price reveals nothing about the nature of the demand curve above list price) to being (much more nearly completely) inelastic at any time, based on the number of items offered for sale via alternative means. We treat this number, for the present, as being exogenous. As this inelastic supply moves around, it will trace out points on the demand curve for the product. Thus achieved auction prices reveal the nature of demand.

This information concerning the nature of consumer valuations is potentially useful to the ultimate seller of the good, in this case, Apple. Like any seller of a new product, it has to gauge an appropriate level of price. One strategy in doing this (with a durable good) is to pitch price high, and reduce it over time, hoping to move down the demand curve. Alternatively, it may wish to set price conservatively, in order to encourage early adoption and market interest and to avoid reputational loss. In this case, it is useful for the seller to get some insight into the direct money loss involved, to compare with the potential benefits. In our particular case, as we see later, the seller is also able to gain important insight into the profitability of its bundling strategy.

3. Characteristics of the dataset

The sample of auctions from which to capture our data was constructed as follows: The iPhone4 went on sale in the UK on 24th June 2010.[8] We started monitoring sales on eBay from this date and continued until early August 2010, the last recorded sale closing on 7th August, 44 days later. There

[7] At least at the time of sale; there may be a “snob” value in being an early adopter.
[8] This was shortly after the US but before a number of key markets including Hong Kong and Australia.

was considerable activity regarding both iPhone4 16GB and 32GB versions, so that in order to preserve all the cases two research assistants were used. One attempted to capture all relevant cases by "watching" then subsequently recording them (it is possible to "watch" up to 200 auctions at any one time, so there is time to record the information on each) whilst the other engaged in screen scrapes using Python, a computing language, parsing the HTML pages- this latter approach leaves a good deal of data cleaning to be done.[9] Comprehensive information regarding all bids made on either iPhone4 were collected, including bidder identities, seller identities (both these are truncated by eBay to preserve anonymity), bidder and seller experience, seller's record, bid values, total number of bids per item, all available details of the item including whether "new" or not, whether "locked" or not, postage, whether deliverable outside the UK, etc. Table 2 lists the variables and their definitions.

We collected information on over 2,500 auctions. However, it became apparent that a proportion of these may not have completed in the normal manner. A significant number of "winning" bids were from bidders with very short records on eBay and a proportion of the winners are now classified as "no longer registered" (NLR). Not all NLR cases concerned bidders with short records, but we made the decision to exclude all such cases because we felt there was a significant possibility that someone NLR had reached this status by failing to honour their bid. We therefore take as an implication of a winner's NLR status that the demand expressed in that bidder's price may not be a true reflection of their willingness to pay. Of course it is possible that the item then went to the second highest bidder through the established eBay mechanism (the "second chance offer"), but we are not able to know that. Statistics on the excluded cases are given in table 1.

Since we are concerned mainly with demand revelation, we did not attempt to exclude potentially dubious sellers, although the problem appeared not to be anywhere near as significant on this side. In our analysis, we take the position of including variables that are likely to measure whether the

[9] We can easily avoid double counting by using the 11-digit eBay ID number as a marker.

seller indeed has the product for sale, so that demand is revealed subject to that qualification. The eBay reputation system has the property that sellers face significant potential penalties to future trading activity including having Paypal transactions reversed in their account for listing misdemeanours, losing their reputation (Cabral and Hortacsu, 2010) and having to build it up afresh, through failing to complete their side of the bargain. Given the prior literature findings, we incorporate asymmetries into our measures of reputation

Because of the very significant consumer interest, expressed in excess demand for the product, achieved sale prices were very high, but with a significant variance, as we pointed out in Table 1.

4. The model

Our model takes a fairly conventional form, as represented in the equation below.

$$P_{i,t} = f(t, i, locking\ characteristics, UK\ only, "new", seller\ reputation, bidder\ nos, start\ P, bin, returns)$$

We seek to explain the winning bids made, $P_{i,t}$, primarily through factors influencing the demand for the product.[10] Demand differs as between the 16GB and 32GB products (the *i* variable). Clearly, it is possible that demand is influenced by immediacy (or "snob value")- although the product was in short supply in the early period, this was unlikely to persist. Therefore, demand may depend on the period elapsed since the product arrived, the *t* variable. "News" also has a potential impact- there was a widely reported issue, embarrassing to Apple, regarding the antenna when the phone was held in a certain manner. This reached a crescendo in mid July and Apple held a press conference on

[10] A note on postage: We decided against including the figure for postage in our analysis. This was for several reasons. First, the data on postage charges shows rather little variation- the minimum price being zero and the maximum £9, with £7 being the modal figure. Notice that this amounts to around 1% of the achieved price (and the correlation of delivered price with net price is extremely high). Second, there are some missing observations on postage and some sellers proposed the buyer collect- it is difficult to know what figure to insert here. Third, there is some evidence that postage is treated differently by buyers (e.g. Hossain and Morgan, 2006).

16th July 2010 in connection with the issue. We attempt to capture time effects through the means of a non-linear relationship with time in the regression and a specific "news" dummy.

An "unlocked" phone is likely to be more valuable than a "locked" one, since the purchaser has freedom to use any network and need not bear the potential expense/ concern about unlocking the product to use it on an alien network. Being locked to different providers may matter- because of the initial exclusivity policy set by Apple in selling the iPhone 3 it is overwhelmingly O2 users who have most experience of the previous iPhone in the UK and may be nearing the end of their current contract. A "new" phone, under eBay's definition, may be slightly more valuable than one that has never been used (although of course, none is old). Since the rollout of the iPhone 4 was gradual around the world, and some countries had not yet had the opportunity to purchase, sales where the supplier was willing to send the phone abroad might achieve a higher price.

Some purchasers may be concerned that the seller does not have the good or is supplying a look-alike. Real (ie non-stock) photos may be convincing here, [11] as will an excellent previous reputation. We develop and experiment with three separate measures of reputation to capture the potentially asymmetric effect, namely the percentage good feedback, whether the feedback score of the seller is perfect, and a count of the number of "stars" the seller has- we report results relating to the last two of these three.

In line with the established literature, we include the minimum bid (i.e. the starting price), the duration of the auction and the "buy-it-now" (bin) price (as a possible proxy for reserve price). Although they have a relatively limited role in theoretical models, we include the number of bidders bidding for the auction, the number of bids and whether there is a returns possibility.[12]

[11] Given that our interest is in willingness to pay, we are not over-concerned about whether the transaction failed to complete due to a fault on the seller's side, although what evidence is available suggests the seller acted in good faith in the vast majority of cases.
[12] A larger number of bidders will tend to raise the price nearer to the winning bidder's valuation. The reserve price, which can influence the outcome, is generally unknown but must be distinguished from the start price, which we do know.

The supply side

Assume the (genuine) seller obtains their phone on the UK market, probably through pre-ordering, at list price. Acting in an arbitrage role, the seller wishes to create a floor under their likely revenue at the list price. In practice, auctions with an opening bid this high are unlikely to generate much interest; a hidden reserve may be better.[13] The seller could introduce a "buy-it-now" price, and some do; under the eBay system, this disappears once/ if bidding starts. The other major instrument at the seller's disposal and not covered already is when to offer the good for sale. In this particular case, the seller faces a tradeoff between a desire to capture the market early when snob value is high, versus potential problems of the market being too crowded or adverse news having an impact on the price. It is likely that, following reports of problems with the iPhone 4, sellers will temporarily hold back stock in the hope that Apple finds a solution quickly. This is exactly what appears to happen. Figure 1 shows cumulative sales closed against elapsed days in this market- both versions are very similar in that there is a distinct hiatus after around day 20 (14th July) that lasts for a week or so before there is a second takeoff in (offers for) sales again until around day 33, when there appears to be a more natural cooling off in the market.[14] We also introduce the number of sales closing on that day into the regression explaining price, although the impact is potentially ambiguous.

5. Results

The regression results, either separately for each version or for both versions combined, provide a good fit and broadly sensible coefficient values, in line with existing studies of eBay auction behaviour. Table 3 lists the main results for the regression analysis. Because there is evidence of heteroskedasticity in the residuals, we report the results on the basis of robust standard errors. We

[13] Casual observation of conventional open-outcry auctions shows that the auctioneer normally needs to warm up the bidding by starting low, or going below an initial suggestion, before the price starts to rise through that point again.

[14] Of course, the day the sale closed is at least one day after the product was put up for sale.

report regressions explaining both the winning price (winpr) and the natural log of the winning price (lnwinpr). Specification tests and histograms of the price distribution suggest the semi log form of the regression is more acceptable, but unfortunately it makes interpretation of coefficients less straightforward.[15] In columns 3 and 4 we report semilog results for the 16GB and 32GB models separately, as well as together, but as can be seen in table 3 they are rather similar to each other so we focus on the results for the whole sample and all the numerical magnitudes are derived using this combined sample result on the log version.

The variables that are statistically significant and positive include the condition (whether it is "new" or not), whether there is a real photo, whether it is unlocked, whether the feedback is perfect, the amount of time elapsed since the phone was released (but affected negatively by the news of an aerial problem), the number of bidders and possibly the number of bids, the start price and whether it is a 32GB model. Being confined to UK only has a negative impact, as do the phone being on Vodafone, the number of phones on sale that close that day, and the number of "stars" a seller has. Longer auctions do not yield significantly higher prices, in our case.

However, not all these things have an economically significant impact, and the interpretation of some is a little complex. To make evaluation easier, assume the base case is a 16GB phone that is new, real and unlocked but confined to the UK (the implicit condition a phone purchased from the Apple store would be in, if freely available). Using our point estimates in the semilog form, this would be valued on average at £608.85. If instead it was a 32GB model, it would be valued on average at £711.73, other things equal.[16] These values are both, of course, substantially in excess of the price charged in an Apple store (and in excess of the observed means across our samples), but that would involve a wait of indefinite time for the phone, at least three weeks depending on version

[15] In the linear functional form case, the coefficients can be read directly as premia applied to a particular characteristic (e.g. whether the phone is unlocked), but with the log form, the impact of a particular feature depends on the other features with which it is associated.
[16] Notice this is very similar to the figure obtained from the linear functional form.

and source. If the phone could be taken/ sent overseas, then the value would increase significantly, to £676.08 and £790.32 respectively.

Returning to the base case of a 16GB phone, new and real but now assuming it is locked to Vodafone, the model suggests its value would fall to £502.61, a very significant fall indeed. Being locked to O2 leads to a significantly lesser fall in price than this, which makes sense given the institutional position discussed in section 4 above. Going back to the base case, adding five more bidders (a little above one standard deviation) raises the price to £618.24, that is rather slightly, and in line with the idea that more bidders will lead to the winning bidder paying somewhat nearer to their valuation for the good. Adding more bids leads to a similar conclusion. The impact of a different start price is statistically but not economically significant, in line with general presumptions of auction theory. Statistically, the number of stars a seller has influences price negatively which is a puzzle, but economically it is not significant in size. However we should recall that this is conditioned on the feedback being "perfect", which did have an economically as well as statistically positive impact; the overall impact of a better reputation is still positive (and non-linear). It makes sense that the more sales closing that day, the lower the achieved price, although the measured impact is small.

As a final influence on the outcome, consider the effect of time. The values above were generated assuming purchase at day 1. The elapsed time and its square are both statistically significant, but of opposite sign, suggesting an *increasing* value over time, but at a decreasing rate. To this must be added the impact of the negative news regarding the aerial problem. Thus the effect is a little complex. Taking the base case again, by day 15 the value of the phone has risen to an average of £676.03. By day 20, the news effect has kicked in and the value is now £654.35. In doing this calculation (and indeed previous ones), we have not taken into account the effect of different numbers of auctions closing on any particular day, although as pointed out already, these shrink around the period of the news. Considering this effect separately in relation to the base case, if we assume the mean number of (approximately) 50, the base case value would move to £592.81.[17] One standard deviation (24 sales) either side, the values are £600.45 (with 26 closing) and £585.26 (with 74 closing).

6. Some Interpretations

The modelling confirms the obvious impression from the raw figures of the eBay auctions leading to a very substantial average premium on the price of the phone, indicating significant excess demand for the phone translating in turn into the auctions being won by people with valuations for it substantially in excess of the Apple's listed retail price(s). The model confirms a number of existing findings on eBay auctions and yields sensible values for factors such as seller reputation, the number of bidders, auction start price etc. However, beyond this, in the context of most existing work on eBay auctions, the significant excess demand, arguably leading to a significant extent of revelation of the nature of demand above market price by individuals, is a novel finding. It naturally leads to the question of why Apple did not charge more for the phone, at least initially. Possibly, total demand at these prices is relatively thin, so that it was not worthwhile to engage in a time discrimination strategy. Or perhaps Apple was concerned about negative publicity.

Nevertheless, the results also cast an interesting light on the discrimination strategy that Apple *is* practising, in respect of price differentials between the 16GB and 32GB versions of the phone. With the iPhone, memory is bundled with the phone and cannot be changed. The list price differential between versions is £100. This is large in relation to Apple's likely cost difference between them. Many other broadly similar "smartphones", for example the HTC Legend running Android, allow the user to determine the amount of memory to insert in the phone. The HTC Legend can take up to 32GB of micro SDHC memory. This size memory is widely available on the internet. In mid-August 2010, the postage paid price of a 32GB micro SDHC memory card of reputable make was around £82

[17] Clearly, in the base case of purchase from the Apple store, this variable makes no sense- it only makes sense in the auction context.

(e.g. on Amazon, £84). This contrasted with 16GB of micro SDHC at around £30. So the difference in price between purchasing one and the other is only just over one half of the difference Apple charges. The eBay auction results suggest that, at least with these early customers, the substantial £100 price differential was fully justified (in management terms) by the difference in willingness to pay as between the different versions.

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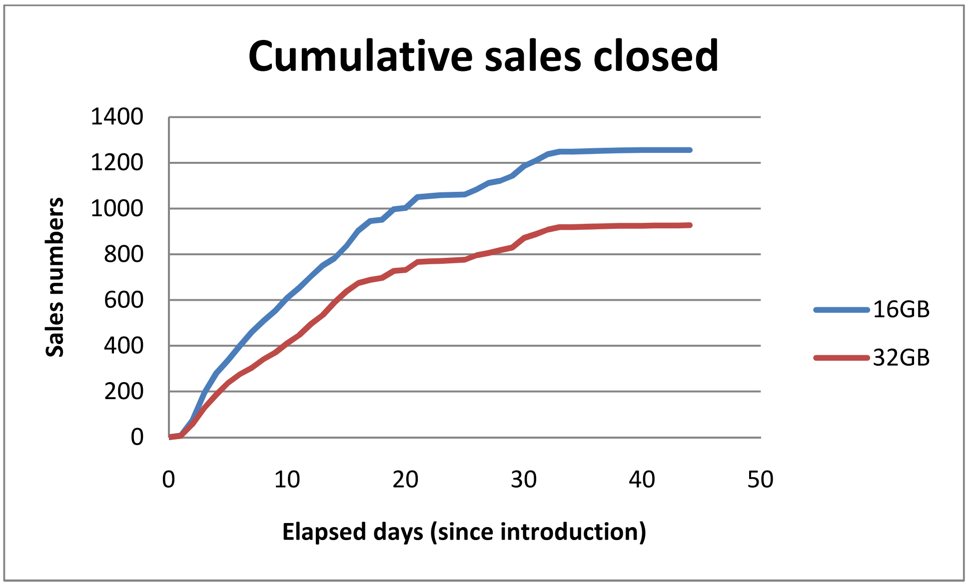

Figure 1: The pattern of sales across time in our samples

Characteristics of the samples	**Version**	
	16GB	**32GB**
Auction numbers used in analysis	1256	927
No longer registered/ dropped*	223	94
	15.1%	9.2%
Mean transaction price	£640.35	£778.73
Min price observed	£100	£480
Max price observed	£1,180	£1,551
Apple website price (sim free)	£499	£599
In excess of Apple retail price	1235	903
	98.3%	97.4%
Max daily sales	118	71

*See the Data section for more details

Table 1: Characteristics of the samples of iPhone 4 auctions analysed

Variable definitions

Name	Definition
winpr	Final winning price to buyer, excluding postage
ID	11 digit item number on eBay
nonstock photo	Number of non-stock photos
total photo	Number of photos of any type
realphoto	dummy takes value 1 where there is at least one non-stock photo
network	network to which the phone is locked, according to seller
unlockdum	phone declared to be unlocked
o2dum	locked to O2 network
vodadum	locked to Vodafone network
orangedum	locked to Orange network

(The default is that the phone is locked to another network, eg AT&T, or is not declared)

worldwide	deliverable anywhere in the world = 1, 0 otherwise
ukonlydum	deliverable to UK only =1 (remaining case is deliverable in, say, EU, or US)
postage	postage charge for UK delivery
returns	Will seller accept a returned product?
condition	declared condition, according to eBay definitions (eg used)
conditnd	condition declared as new = 1, 0 otherwise
userid	The (middle truncated) identity number of the eBay seller
posfeedbak	Proportionate feedback on seller to date
feedbkd	is 1 if feedback = 1, 0 otherwise
star	eBay seller's "star" rating (a measure of the number of transactions undertaken)
duration	number of days for which auction lasts
biddernum	number of discrete bidders
bidsnum	total number of compliant bids (not including proxy bids)
startp	price at which auction commences
bidderid	The (middle truncated) identity number of the eBay buyer (together with

	information about bidder experience)
Endtime	time and date of end of auction (time/ date of final bid and of start also recorded)
bindum	product has buy-it-now price
elapst	time in days since 24th June (introduction date into UK)
elapstsq	square of the above
closingnum	number of auctions closing some time in that particular day
lxxx	natural log of variable xxx

Table 2: Definitions of the variables employed

	Dependent Variable							
	winpr		lwinpr		lwinpr16		lwinpr32	
Variable	**coeff**	**t-stat**	**coeff**	**t-stat**	**coeff**	**t-stat**	**coeff**	**t-stat**
conditnd	41.87	4.09	0.0629	4.31	0.0579	2.72	0.7283	3.99
returnsd	4.01	0.67	0.0069	0.86	0.0123	1.60	0.0009	0.08
realphoto	21.38	6.31	0.0328	6.20	0.0313	4.13	0.0342	4.80
ukonlydum	-37.40	-4.17	-0.0545	-4.28	-0.0678	-4.02	-0.0388	-1.98
unlockdum	95.52	11.52	0.1394	11.51	0.1331	8.53	0.1468	7.43
o2dum	-6.22	-0.74	-0.0061	-0.50	-0.0089	-0.58	-0.0034	-0.16
vodadum	-32.98	-3.60	-0.0527	-3.90	-0.0564	-3.36	-0.0493	-2.20
orangedum	-14.73	-1.71	-0.0223	-1.77	-0.0302	-1.95	-0.0084	-0.37
feedbkd	13.79	3.33	0.0201	3.33	0.0195	2.56	0.0217	2.15
elapst	9.22	12.73	0.0131	11.79	0.0136	7.91	0.0134	9.64
elapstsq	-0.29	-13.32	-0.0004	-13.15	-0.0004	-9.34	-0.0004	-10.91
bindum	8.78	1.15	0.0082	0.81	0.0133	0.92	0.0042	0.27
newsdum	-25.95	-3.11	-0.0403	-3.53	-0.0459	-3.33	-0.0344	-2.03
closingnum	-0.40	-4.87	-0.0005	-4.63	-0.0005	-3.36	-0.0006	-2.23
worldwide	46.42	4.40	0.0502	3.52	0.0355	1.83	0.0655	3.05
star	-0.0003	-3.69	-2.98E-07	-3.41	-2.72E-07	-0.10	-3.32E-07	-0.17
duration	0.72	0.81	0.0008	0.71	0.0014	0.88	0.0003	0.17
biddernum	2.01	2.22	0.0031	2.49	0.0021	2.49	0.0005	2.13
bidsnum	1.55	3.24	0.0019	2.89	0.0021	1.40	0.0015	1.43
startp	0.08	8.25	0.0001	7.78	0.0001	4.32	0.0001	6.69
32gbdum	109.91	32.34	0.1561	32.01	-		-	
const	484.50	23.78	6.2310	208.52	6.2551	146.39	6.3463	149.54
R sq	0.6914		0.6826		0.5190		0.5908	

F	195.19	262.69	110.40	68.90
Observations	2183	2183	1256	927

Note: t-statistics based on robust standard errors. For coefficient definitions, see Table 2.

Table 3: **Regression results on the iPhone 4**