

The Economics of Internet Markets*

Jonathan Levin[†]

August 5, 2010

Abstract

The internet has facilitated the creation of new markets characterized by improved measurement, increased customization, rapid innovation and more conscious market design. I describe these changes and some of the economic theory that has been useful for thinking about online advertising, retail and business-to-business platforms, job matching, financial exchanges and other online markets. I also discuss the empirical evidence on the operation and efficiency of these markets and some of the open questions for theoretical and empirical research.

(JEL Classification: C78, D40, D44, L10, L14, O33)

*This paper was prepared for the Econometric Society 2010 World Congress. I thank Andy Skrzypacz for suggestions, and Marissa Beck for excellent research assistance. The National Science Foundation and the Toulouse Network for Information Technology provided research support.

[†]Department of Economics, Stanford University, Stanford CA 94305-6072. Email: jdlevin@stanford.edu.

1 Introduction

Technological changes often lead to the creation of new markets. A recent and striking example has been the emergence of internet markets or platforms for search, retail commerce, job matching, social networking, financial trading, and other purposes. The growth of these platforms has been dramatic. Amazon opened in 1995 and its sales are currently around twenty-five billion dollars a year. China's Taobao started in 2003 and today has two hundred million active users. Facebook, founded a year later, has over five hundred million users. Over the same period, the number of Google searches, and the revenue Google generates from its advertising auctions, has doubled roughly every eighteen months.¹

This growth of internet markets has generated considerable attention from economists, and a great deal of recent research. Some of this work has focused on the market structure of platform industries, and the strategic issues that arise when platforms compete for users. Other strands of research have focused on novel market institutions, such as the keyword auctions run by the major search engines, eBay's consumer marketplace, and the retail competition created by price comparison sites. In this paper, I try to collect and tie together some of the lessons from these different lines of research, and identify some of the interesting open questions.

I begin the paper by describing some of the features of internet markets that I view as particularly salient and distinctive. One reason to start with this is that, after all, there is nothing new about platforms for bringing together buyers and sellers. Shopping malls, trade shows, and newspaper circulars did the same forty years ago. Merchant fairs did so four hundred years ago. Nevertheless, technology does facilitate changes in the way that markets can operate. One such change relates to scale. The internet makes it possible, and often cost-effective, to operate markets with millions of participants, and perhaps millions of products, drawn from around the world. Of course, just because this is possible does not mean it had to happen, so one goal of recent research has been to identify ways in which increasing returns might arise in operating a platform or marketplace.

¹These numbers are taken from company annual reports, and in the case of Google (where the available numbers are imprecise) from comScore. Ellison and Ellison (2005) point out that to reach a billion dollars in sales, it took Amazon just five years, compared to nineteen for Walmart.

A second change is the ability to customize individual experiences, which derives from the low cost of changing displayed information, and the ability to capture and utilize detailed market data. So for instance, a retail platform such as Amazon can customize product recommendations based on consumer buying patterns, search engines can deliver results tailored to current and past queries, and advertising platforms can deliver ads targeted to a user's recent browsing behavior. The ability to customize, and to measure the resulting user behavior, gives rise to another distinctive feature of internet markets, which is the potential for experimentation and innovation. In many traditional markets, firms shy away from running controlled experiments because it is costly or because feedback arrives too slowly to be useful. In contrast, the internet makes it relatively easy to try out and test new ideas and make changes in response, creating the possibility of relatively rapid innovation.

I describe these characteristic features of internet markets in more detail in Section 2. I use the remainder of the paper to discuss three related strands of recent research. The first, which I consider in Section 3, is work in industrial organization on how platforms compete to attract users. The unifying idea in this work is that platforms are characterized by network effects. Network effects can be direct, as in the case where users sign up for a social network to interact with their friends, or indirect, as in the case where employers post vacancies on a job matching site because they expect workers to respond, and workers search the site because they expect to find job listings. Theoretical models that incorporate these effects help illuminate some intuitive points about platform strategy, such as why platforms might want to cross-subsidize users depending on the value they create for other users, or why tensions can arise between short-term profitability and longer-term value creation. The theory is also useful for thinking about the market structure of platform industries, and the conditions under which network effects might favor the emergence of dominant platforms.

The standard models of platform competition tend to abstract from the details of how platforms facilitate user interaction and try to create efficient and adaptable marketplaces. In Section 4, I discuss work on mechanisms that platforms use to match users with trading opportunities. A leading example is the auction used by search engines to allocate display space following a user query. The problem is more general, however, in that many internet platforms — not just search engines, but platforms for e-commerce, job matching, social

networking, dating and so forth — are centered around a search function that helps people locate and evaluate products or opportunities. While structuring matching processes falls partly into the domain of statistics (e.g. data-mining techniques to predict relevant matches), it also raises new issues for market design. As examples, I discuss the pricing systems used for e-commerce listings, and the organization of markets for targeted advertising.

The final section of the paper, Section 5, considers a third strand of work on competition and consumer behavior within internet markets. Much of this research has centered on novel market institutions such as price comparison engines, consumer auction platforms, and online recommendation and reputation systems. A main lesson is that while the internet has reduced certain frictions such as the cost of search, or of running auctions, or of aggregating user feedback, the results have not always been predictable. For example, the evidence suggests that price comparison engines can create strong incentives for obfuscation, that the initial excitement over consumer auctions has been waning, and the reputation systems can fall prey to strategic manipulation. In this sense, internet markets have been an interesting laboratory for learning about consumer and firm behavior, and about how to design well-functioning marketplaces.

I should emphasize that this paper is a fairly selective survey. I focus on a particular set of related issues: how internet platforms try to attract users, how they match participants to create exchange opportunities, and how they foster competition and enable trade. In doing this, I put aside many interesting questions about how internet markets have impacted traditional industries, about regulatory policy toward internet platforms, and about their social implications. Each of these topics easily could sustain its own survey.

2 Technology and Internet Markets

The internet reduces a number of traditional costs associated with organizing markets. It is easier for users to visit an online market and search for trade opportunities, easier to update displayed information, and easier to capture and utilize market data. Much of the early economic research on internet markets emphasized the direct effects of these changes — for example, the idea that lower search costs would increase retail competition, or that

lower costs of assembling consumers would facilitate the use of auctions (see e.g. Hall, 2002; or Ellison and Ellison, 2005). In this section, I highlight how these cost reductions have enabled the three features of internet markets mentioned above: scale, customization, and the potential for innovation.

Many internet platforms operate at very large scale. On a given day, the eBay marketplace has around two hundred million product listings, Google runs several billion sponsored search auctions, and around two hundred million users log in to Facebook. That this is even possible is the result of conscious engineering. Most platforms are designed so that they can scale at relatively low cost. Facebook, for example, employs less than one engineer for every million users.² Of course, the fact that a platform can scale to accommodate millions of users doesn't mean that they will show up. This raises the question of why certain types of activity become concentrated on particular platforms, or in particular marketplaces.

Most explanations involve some form of increasing returns. One potential source of increasing returns derives from the cost structure of operating an internet platform. Investments that increase quality and efficiency, such as improving site design, collecting and analyzing data on user behavior, or undertaking experiments to test innovations, involve costs that are relatively fixed, but benefits that are scalable. These activities may also be cumulative, or involve a certain amount of learning by doing. A second potential source of increasing returns, and the one that economists have tended to emphasize, is network externalities. Network externalities, which I discuss in the next section, be a convincing source of increasing returns in many cases (say, in the case of social networks), but arguably a less obvious source in some others (say, in local markets for jobs or real estate).

A second distinctive feature of internet markets is the degree to which user experiences can be customized. In traditional markets, it tends to be costly to personalize individual experiences. So every visitor to the mall sees the same displays, and everyone listening to a radio show hears the same commercials. On the internet, users are shown search results tailored to specific queries, offered recommendations based on past behavior or expressed preferences, or provided with information about the experiences of similar consumers. From

²“Scaling Facebook to 500 Million Users and Beyond,” blog post by Robert Johnson (July 21, 2010) at http://www.facebook.com/note.php?note_id=409881258919.

an economic perspective, one way to think about this is from the perspective of matching: customization facilitates a more efficient matching of users and opportunities. The research that I discuss in Section 4 focuses on the use of market mechanisms designed for this purpose.

The ability to customize is also a function of the available data. Virtually every internet platform collects extraordinarily detailed data on user behavior and activity,³ which can be mined to identify potentially successful matches. This is the idea that underlies Amazon or Netflix’s recommendation functions, Google’s search algorithms, Facebook’s friend finder, and targeted advertising. The collection of user data, and more generally the ability to measure behavior, also has other economic implications. For instance, Varian (2010) describes how it enables new forms of contracting, such as “per click” payments for advertising, and Acquisti and Gross (2009) considers some of the privacy concerns that it raises.

The third feature of internet markets that I want to emphasize, and one that has received less attention, relates to innovation. By innovation, I have in mind both the creation of new products and ideas, and the gradual refinement of things like search algorithms, the information displayed to users, market rules, pricing mechanisms and so forth. The same technological changes that reduce the costs of customization also reduce the cost of adaptation over time. Making quick adaptations, however, is only useful if information arrives on a similar time-scale. A striking feature of many successful internet platforms is their use of randomized experiments to improve the flow of information. Economists are often puzzled (and empiricists frustrated) by how little systematic experimentation occurs in traditional markets. But as I suggested above, experiments can be costly and the feedback loop can be too slow to generate benefits. When a few lines of code result in different groups of users seeing different displays or facing different prices, and the results are measured instantaneously, it becomes much easier to use experiments to facilitate adaptation and innovation.

Finally, one additional feature of internet markets that makes them interesting for economists is the extent to which platforms can control different aspects of exchange, from structuring user search, to controlling and monitoring transactions, to experimenting with market

³As this data becomes more broadly available, it is likely to be a rich source for economists interested in a wide range of market and non-market questions. Some recent examples of the latter include Ariely, Hitsch and Hortacsu (2009), who estimate consumer preferences based on their internet dating choices, and Gentzkow and Shapiro (2010), who estimate ideological segregation based on internet browsing patterns.

rules and parameters. The result is that internet markets often involve more conscious and detailed market design than is typical of many traditional marketplaces. It also provides economists with the ability to study aspects of pricing, or matching, or competition, or consumer behavior in relatively structured settings where there is extremely rich and fine-grained data.

3 Competition for Platform Users

The economics of platforms has been one of the most active areas of research in industrial organization over the last decade (see e.g. Caillaud and Jullien, 2003; Rochet and Tirole, 2003, 2006; and Armstrong, 2006).⁴ This work was motivated initially by an interest in payment systems such as Visa and Mastercard, and other “two-sided” businesses such as yellow pages and newspapers. Similar to internet platforms, these businesses intermediate between multiple user groups (consumers and merchants, or readers and advertisers), charging fees for platform activity. Importantly, they also feature network effects. Different types of users join the platform to interact with other users, so the value that a platform creates depends on the size and composition of its user base. The research I describe below starts from this basic observation and tries to identify its implications for platform strategy, and for market structure.

3.1 Price Theory of Platforms

In this section, I sketch a basic model of platform pricing that is useful for highlighting some of the strategic issues that platforms face in trying to simultaneously attract users and generate revenue. The model is taken from Weyl (2009), who builds on Rochet and Tirole (2003, 2006) and Armstrong (2006).

Consider a single platform with K groups of potential users. Each potential user has to

⁴See Evans, Hagiu and Schmalensee (2006) Rysman (2009) for informal overviews. The recent literature builds in part on earlier work on network effects, summarized for example in Farrell and Klemperer (2007). The modeling approach I discuss below is also related to work on contracting with externalities (Segal, 1999). One difference is that in Segal’s model, a principal can offer distinct contracts to individual agents, whereas in the platform model I describe below the platform can only distinguish between user groups, leading to a more standard price theory analysis.

choose whether or not to join the platform. The benefits of joining depend on the overall participation. Let x_k denote the fraction of group k users who choose to participate, and $x = (x_1, \dots, x_K)$. For an individual in group k , the payoff from joining is $u_k(x, \zeta) - p_k$, where ζ are the individual's characteristics, and p_k is the fee that the platform requires of group k users. The payoff from not participating is zero. The platform also incurs costs from serving its users: if participation is x , the platform's costs are $C(x)$.

In this model, all of the details of what the platform does, and how users interact, are incorporated in the payoff functions u_k , and the cost function C . Even platform fees have no direct effect on user interactions. If there are distinct groups of buyers and sellers, imposing a fee on sellers only affects buyers if it causes some sellers to exit the market. So we are abstracting from issues around market organization and efficiency that I address later, and focusing squarely on network effects and user participation.

Continuing with the model, we derive user demand for the platform. Let $p_k(x_k; \hat{x})$ denote the highest price at which a fraction x_k of group k users will participate, given expected participation \hat{x} . The inverse demand $p_k(x_k; \hat{x})$ will be decreasing in x_k , but may be increasing or decreasing in \hat{x} depending on the sign of the network effects. We can also let $P_k(x) \equiv p_k(x_k; x)$ be the maximum price that can be charged to group k if the platform implements the allocation $x = (x_1, \dots, x_M)$.

The profit maximizing participation level solves:⁵

$$\max_x \sum_k x_k P_k(x) - C(x). \quad (1)$$

The first order conditions for this problem equate the marginal revenue for each user group $k = 1, \dots, K$, or $P_k(x) + \sum_j x_j \cdot \partial P_j(x) / \partial x_k$, with the marginal cost $MC_k(x) = \partial C(x) / \partial x_k$. It is more insightful, however, to express these conditions in a way that distinguishes the usual trade-off in maximizing profit against a downward-sloping demand curve from considerations

⁵There also may be a question of how a platform can implement a given participation level x . If it sets prices for different user groups equal to $P_1(x), \dots, P_K(x)$, there may be multiple participation equilibria, including an equilibrium in which participation is in fact x , but perhaps also including other equilibria with lower (or higher) participation. A platform can uniquely implement x by making prices contingent on realized participation. One way to do this is to say that if realized participation rates are \hat{x} , then group k users must pay $p_k(x_k, \hat{x})$ — Weyl (2009) refers to this as the “insulating tariff”.

involving network effects. Holding expected participation fixed at \hat{x} , the marginal revenue for group k is

$$MR_k(x_k; \hat{x}) = \frac{\partial}{\partial x_k} (x_k p_k(x_k; \hat{x})) = p_k(x_k; \hat{x}) + x_k \frac{\partial p_k}{\partial x_k}(x_k; \hat{x}). \quad (2)$$

The platform's first order conditions then be re-arranged to yield:

$$MR_k(x; x) = MC_k(x) - \sum_j x_j \mathbb{E} \left[\frac{\partial u_j}{\partial x_k}(\zeta, x) \mid u_j(\zeta, x) = P_j(x) \right]. \quad (3)$$

So the platform's optimal strategy equates the marginal revenue obtained under a fixed (and rational) expectation about participation with the marginal cost of additional users, where the marginal cost is augmented to reflect the fact that when an additional user joins, this alters the value of marginal participants, allowing for a price offset.

The analysis helps illuminate several intuitive points. One is that platforms should subsidize users who create value for other users. Search engines, for example, subsidize consumers by providing free search results and additional services such as email and content. They generate revenue from advertisers and, as I discuss below, typically use a pricing mechanism that penalizes less desirable or relevant ads. Financial exchanges engage in similar cross-subsidization. They typically offer low fees, or even payments, to traders who post limit orders and provide market liquidity, while charging higher fees for crossing orders that reduce the depth of the order book.

A second point is that there can be tensions between current profitability and long-run value creation. Suppose, for example, that the initial platform adopters are relatively price-inelastic, and that the platform cannot offer discounts to new users. In the short-run, the platform may benefit from raising fees (or making equivalent strategic changes) to extract revenue, even if this slows the growth of the platform. This is a standard temptation in switching cost models, but it has an added element here because strategies that reduce the user base can degrade the quality of the platform for continuing users.

The model also highlights two familiar distortions from profit-maximization (Weyl, 2009). The platform internalizes the marginal revenue from additional users rather than their marginal surplus, and it focuses on the externality that they impose on marginal rather than

average participants. At an efficient allocation, we would have

$$P_k(x) = MC_k(x) - \sum_j x_j \mathbb{E} \left[\frac{\partial u_j}{\partial x_k}(\zeta, x) \mid u_j(\zeta, x) \geq P_j(x) \right], \quad (4)$$

so that group k is charged the marginal cost $MC_k(x)$ minus the externality they impose on other users.⁶

As I have described the model, it provides insight into the overall fees a platform should charge to different user groups, but not into the fee structure, which can be an important consideration. In e-commerce, for example, some platforms such as the Alibaba charges sellers an annual fee. Other platforms, such as Craigslist, requires a payment for certain listings. Yet another approach is to charge sellers for clicks (common on price comparison sites), or a sales commission (the model used by Amazon, eBay, Etsy and others). These different pricing structures have different informational requirements — charging a commission, for instance, requires the platform to monitor transactions — but they also create very different incentives for sellers. This aspect of pricing, which I discuss in the next section, is more easily captured in a model where users make decisions about the nature and intensity of platform use rather than a binary participation decision.

A related set of issues pertain to user heterogeneity. On an e-commerce site such as eBay, sellers range from professional businesses to individuals emptying their garages. In some cases, these users might be identifiably different (i.e. belonging to different groups), but in other cases the distinction may be less clear. Similarly, on a job matching or dating platform, some candidates will inevitably be more attractive. Although platform pricing may be one instrument to favor or discriminate between different users, screening decisions or the design of the search process may be equally or even more important. These issues of user heterogeneity are likely to be particularly important if researchers begin to bring empirical methods to bear on studying platform pricing decisions or estimating the size and

⁶To see how this expression is derived, let $V_k(x) = \int \mathbf{1}\{u_k(x, \zeta) \geq P_k(x)\} u_k(\zeta, x) dF_k(\zeta)$ denote the gross surplus generated by group k users if the total participation is x , and let $V(x) = \sum_k V_k(x)$. The equation in the text come from re-arranging the first-order condition for an efficient allocation, namely that $\partial V(x) / \partial x_k = MC_k(x)$ (see Weyl, 2009, for more detail). Note that one might question whether the ‘Spence distortion’ of focusing too much attention on how changes affect marginal users is really empirically relevant, or is outweighed by the ability of dedicated users to exert influence in ways that do not involve threatening to exit.

scope of network effects. So far there has been very little of this in the context of job search sites, e-commerce platforms, advertising exchanges, or electronic financial markets, but there would seem to be many promising opportunities given the potentially available data.

3.2 Platform Competition and Market Tipping

The model above provides a useful starting point for thinking about what happens when multiple platforms compete to provide the same or similar services. Recent research has emphasized how, in addition to typical competitive factors such as the intrinsic appeal of the platforms and their cost structure, competitive outcomes can depend on the strength of network effects and the extent to which users “multi-home”. For example, in internet search, consumers might tend to use a single search engine, while advertisers might be willing to multi-home and advertise on several platforms. Armstrong (2006) and others have pointed out that in this type of setting, competition can be asymmetric: platforms have an incentive to compete aggressively for single-homing users, but then enjoy a monopoly over these users when they are setting prices for the multi-homing side of the market.

Perhaps the central question in thinking about platform competition is whether network effects (or alternatively, cost economies) will lead to activity becoming highly concentrated, and how this concentration might affect prices and long-term innovation. It is easy to identify examples of (at least temporary) market tipping. In the U.S., eBay quickly captured the consumer auction market despite the presence of many competing platforms, and Google has retained roughly two-thirds of the internet search market despite aggressive investment by Yahoo!, Microsoft and others. In China, the respective markets are dominated by Taobao and Baidu. But there are also examples to the contrary. Prior to the advent of electronic trading, the New York Stock Exchange and Nasdaq played a relatively dominant role in the trading of US public equities. Indeed nearly 80% of trades in NYSE-listed equities took place on the exchange floor. Today, with the entry of new electronic markets, no exchange has more than a 20% share of trades in registered equities. Moreover, even in industries where one might expect agglomeration, such as social networking, it is easy to point to examples of successful entry (such as Twitter) or rapid decline (such as MySpace).

Theoretical models can suggest factors that might favor market tipping, but the pre-

dictions are not necessarily that sharp. For instance, strong positive network effects and a preference for single-homing should favor concentration. But in practice the most obvious network effects may be geographically local, or confined to users with particular needs or interests, and particularly on the internet where switching costs are often quite low, preferences for single-homing may not be that strong. (For precisely this reason, one probably needs to be cautious in generalizing lessons about long-term lock-in from industries with both network effects and high switching costs to the case of internet platforms.) In addition, positive network effects can be offset by congestion. In Ellison and Fudenberg's (2003) model of competing buyer-seller platforms, buyers benefit from additional sellers, but suffer from having to compete with other buyers. In their setting, multiple platforms can co-exist so long as they have approximately equal buyer-seller ratios.

This suggests that an empirical approach is needed to understand the extent to which network effects, or other factors such as increasing returns in the cost structure of platforms, favor a concentrated market structure. A recent paper by Brown and Morgan (2009) makes a start in this direction by using field experiments to compare the experience of auction sellers on eBay and Yahoo!. At the time the experiments were conducted, eBay's platform was roughly ten times the size of Yahoo!'s. Brown and Morgan use their experiments to test if sellers on the two platforms can expect to receive similar numbers of bidders and similar prices, as one should expect if the markets were in a co-existing equilibrium. Instead they find that prices are 20-70% higher on eBay, and eBay auctions attract 50% more buyers. Their study is interesting not just for its findings but because it illustrates the relative ease of using experiments to measure quantities of interest in online markets.

4 Structuring Search and Matching

The platform model described above takes a high-level approach by specifying user benefits as a function of the number and composition of other users. In practice, aggregating users creates potential gains from trade, but to realize these gains users must be able to identify and assess relevant opportunities. In this section, I describe research that focuses on the problem of how platforms can effectively match users with opportunities. I start with

the auctions used by search companies to allocate display space, and then discuss related matching problems that arise in e-commerce and online advertising markets.

4.1 Sponsored Search Auctions

Sponsored search advertisements appear on search engine pages along with the standard algorithmic results. These advertising opportunities are valuable because when a user enters a query, say “hard drive recovery,” he or she reveals a particular interest at a particular time. The major search engines take a market-based approach to figuring out which ads should be shown in response to which queries. They ask advertisers to specify keywords against which they would like their ads to be shown and, building on an approach pioneered in the mid-1990s, run an auction to determine which ads will be shown in different positions.

The evolution of keyword auctions is an interesting case study in market design. An initial innovation, made by the firm GoTo (later Overture), was to have advertisers pay for clicks rather than for display space, as was done in early internet advertising. Clicks are a useful metric in that they provide an “exchange rate” between positions on a web page (Varian, 2010). Even if advertisers would insist on paying different amounts for different positions, they may be willing to offer a single per-click price.⁷ A subsequent innovation, by Google, was a new second price auction format. In Overture’s initial auctions, winners paid their bids on a per-click basis. The auction proved to be unstable, with bids sometimes cycling over the course of minutes (Edelman and Ostrovsky, 2006), leading Google to try something new. Economic theory helps explain why the pay-your bid auction was problematic — it generally has no pure strategy equilibrium, as bidders try to offer the minimum increment above the bidder below them — and as I discuss below, why the second price format has been more successful.⁸

⁷Milgrom (2009) has shown that simplifying bidding in this way can have substantial advantages in terms of increasing competition and eliminating undesirable auction outcomes, particularly if bidding is costly.

⁸Bulow and Levin (2006) analyze the mixed strategy equilibrium of a closely related position auction. They find that it can come quite close to achieving efficient outcomes, although that does not help to solve the instability problem if bidders can change their bids in real time.

4.1.1 The Position Auction Model

Two papers by Edelman, Ostrovsky and Schwarz (2007) and Varian (2007) set out a basic assignment model of sponsored search.⁹ In their model, there are N advertisers who value clicks at $v_1 \geq \dots \geq v_N$. Their ads can be placed in M positions, and the positions receive clicks with frequency $x_1 > \dots > x_M$ regardless of which ad is shown. If advertiser i is placed in position j and pays p per click (or $t = px_j$ for the placement) its payoff is $v_i x_j - t$. The efficient assignment (in terms of maximizing advertiser surplus) is assortative; it places advertiser 1 in the top position, then advertiser 2 and so on.

The efficient assignment can be supported with competitive prices if we treat each position as a separate good. A set of position prices t_1, \dots, t_M will clear the market if and only if for each advertiser k , and each $j \neq k$,¹⁰

$$v_k x_k - t_k \geq v_k x_j - t_j. \quad (5)$$

The model has several appealing properties. First, it is sufficient to consider only the local equilibrium conditions, namely that each advertiser k prefers position k to positions $k - 1$ and $k + 1$. Second, market-clearing prices always exists, and there is always a market-clearing price vector that is component-wise maximal, and another than is component-wise minimal.¹¹ Third, prices must be increasing, on a per-click basis, as one moves from lower to higher positions. To see why, note that advertiser k must be willing to pay for the extra $x_k - x_{k+1}$ clicks obtained in position k relative to position $k + 1$, but not for the extra clicks obtained in position $k - 1$. So the incremental cost of clicks must be increasing as one moves to higher positions.

In practice, one way a platform could set prices would be with a Vickrey auction. In a

⁹In parallel with the research in economics kicked off by these papers, sponsored search auctions have inspired a large literature in computer science. Lahaie, Pennock, Saberi and Vohra (2008) is a fairly recent survey that covers this work.

¹⁰To make this precise, suppose that $N > M$ (without loss of generality because some advertisers can have zero value), and that $x_j = t_j = 0$ for $j > M$.

¹¹For instance, suppose there are two positions that receive 200 and 100 clicks, and three advertisers with per-click values 3, 2, and 1. The price of the lower position must be at least 100 to deter the lowest value bidder, but no more than 200. Similarly, the *incremental* price of the top position must be between 200 and 300 to ensure the market clears. So the lowest equilibrium prices are (300, 100) and the highest are (500, 200).

Vickrey auction, advertisers are asked to report their per-click values as bids b_1, \dots, b_n . The auctioneer implements an efficient allocation given these reported values, and payments are set so that each bidder pays an amount equal to the externality he imposes on lower-ranked bidders by displacing them one position. If we order the bids such that $b^{(1)} \geq \dots \geq b^{(n)}$, the payment for position k is $t_k = \sum_{j \geq k+1} b^{(j)} (x_{j-1} - x_j)$. This payment rule makes it a dominant strategy to report one's true valuation. So the equilibrium payments in the Vickrey auction are $t_k = \sum_{j \geq k+1} v_j (x_{j-1} - x_j)$. These payments correspond exactly to the lowest market clearing position prices.

The major search engines instead use a “Generalized Second Price” (GSP) auction that has similarities to the Vickrey auction but is not the same. The bidders make per-click bids and are assigned to positions on the basis of these bids, but the bidder in position k pays the $k + 1$ st highest bid. With this payment rule, it is no longer a dominant strategy to bid one's value. Instead, a Nash equilibrium of the GSP auction can involve bids above, at, or below a bidder's value.¹² Nevertheless, the analyses of Edelman et al. and Varian help explain why this auction might work well. Both papers focus on a refined subset of Nash equilibria in which no bidder would like to “trade positions” with the bidder above or below. That is, no bidder wants to assume a competitor's position and pay the price it is currently paying.¹³ These refined equilibria correspond in a precise way to the competitive equilibria described above. The assignment of bidders to positions is efficient, and the equilibrium GSP payments coincide with the payments in some competitive equilibrium. Moreover, for any competitive equilibrium, there is a refined equilibrium of the GSP with the same payments.

¹²In the numerical example in Footnote 11, there is a GSP auction equilibrium in which the bidders bid their true values 3, 2 and 1, but also other equilibria including one with bids equal to 4, 2.5 and 2, and another with bids equal to 2, 1 and 1. The last of these has equilibrium payments that correspond to the Vickrey payments, but the others have higher payments and auction revenue.

¹³Edelman et al. refer to these equilibria as “locally envy free”, while Varian calls them “symmetric”. To understand how it works, suppose that $b^{(1)} \geq \dots \geq b^{(n)}$ is a bid vector and $v^{(k)}$ is the valuation of the k th highest bidder. The bids constitute a Nash equilibrium if for all k , $(v^{(k)} - b^{(k+1)}) x_k \geq (v^{(k)} - b^{(k+2)}) x_{k+1}$ and $(v^{(k)} - b^{(k+1)}) x_k \geq (v^{(k)} - b^{(k-1)}) x_{k-1}$. The refinement strengthens the second condition to require $(v^{(k)} - b^{(k+1)}) x_k \geq (v^{(k)} - b^{(k)}) x_{k-1}$. But this means that the conditions for a refined equilibrium are identical to the conditions for a competitive equilibrium with per-click prices $p_k = b^{(k+1)}$ or position prices $t_k = b^{(k+1)} x_k$.

4.1.2 Connecting the Theory to Data

Several recent papers, including Varian (2007, 2009), Borgers, Cox, Pesendorfer and Petricek (2008), and Athey and Nekipelov (2010), describe how the position auction model can be applied to search engine data. The idea is to use bidders' revealed preference to infer their valuations. Suppose a bidder with per-click value v , by bidding b can expect to receive $X(b)$ clicks and pay $C(b)$. If we think of the bidder as choosing a quantity of expected clicks x (i.e. by making a bid b such that $X(b) = x$), then its choice problem is $\max_x vx - c(x)$, where $c(x) \equiv C(X^{-1}(x))$. Assuming that the cost function is well behaved (i.e. smooth and convex) the optimum satisfies $v = c'(x)$.¹⁴ The bidder should buy clicks up to the point at which the marginal cost of clicks equals its click value. So if we can estimate $X(b)$ and $c(x)$, we can find the click values that rationalize different bids by using the first order condition.

Figures 1 and 2 demonstrate the approach using data derived from Google's online bidding tool.¹⁵ Figure 1 shows the expected cost curve $c(x)$ for three different keywords. The marginal cost of clicks reported by Google is generally but not always increasing, so the figure also shows a fitted cost curve that imposes convexity.¹⁶ Figure 2 plots the expected cost on a per-click basis (i.e. $c(x)/x$) along with the click values that rationalize the purchase of each expected quantity (i.e. the value v such that $v = c'(x)$).

The analysis is meant to be illustrative, but in principle this type of approach can be used to address a set of important questions, such as the extent to which search engines are able to appropriate the surplus created by matching advertisers and users. The data in Figure 2 suggest that for bids in the displayed ranges, the platform's share of the surplus is on the order of 15-35%. Varian (2009) reports similar numbers based on internal Google data. He notes that the platform's share is greater for keywords in high demand. Athey and Nekipelov

¹⁴In the perfect information model above, the cost function a bidder faces in equilibrium is convex (i.e. has increasing marginal cost of clicks) but is not continuous. Intuitively, a small amount of uncertainty should smooth the discontinuity, and indeed Athey and Nekipelov present a version of the model with imperfect information in which bidders have a continuously increasing and convex cost of clicks in equilibrium.

¹⁵Google's Traffic Estimator is available on the Google Adwords site. The tool allows one to input candidate bids and obtain the estimated clicks and cost per day. Google provides the estimate in the form of an interval. I used the midpoint of the range. The data were downloaded in May 2010. The keywords are "Auto Insurance", "VOIP phone" and "Mesothelioma". Mesothelioma is a rare form of cancer caused by exposure to asbestos, and a keyword that is in high demand from plaintiff lawyers.

¹⁶The fitted curve is the piecewise linear convex curve that is minimizes squared deviations from the data (see, e.g. Dent, 1973).

(2010) report a wide range of estimates for selected keywords, but their mean estimate of the platform’s share also appears to be on the order of 30%. Their econometric approach is considerably more sophisticated than what I have described, in that they write down an explicit model of bidding under imperfect information, and prove that its equilibrium first order conditions identify the bidder values.

4.1.3 Extensions of the Sponsored Search Model

Several aspects of the sponsored search problem can be tied back to the discussion of network effects and platform strategy. First, the sponsored search model focuses on the relationship between the platform and advertisers. Chen and He (2006) and Athey and Ellison (2009), however, have developed extensions of the model that explicitly incorporate consumer choices (see also Gomes, 2009). In Athey and Ellison’s model, consumers want to match with a compatible product, and given the ads displayed by the platform, they search rationally.¹⁷ This type of model provides a framework to think about how the platform’s market design choices impact users. For instance, Google historically showed more “white space” (i.e. blank positions) than Yahoo! or Microsoft. While one effect of limiting the available space might be to raise the price for advertisers, doing so can also create value for consumers by filtering out irrelevant ads. Athey and Ellison observe that reserve prices sometimes can be welfare-enhancing for a similar reason. (See also Ostrovsky and Schwarz, 2010, for a revenue perspective on reserve prices.)

A key insight from previous section was that platforms should reward users that create value for others. One way that search engines do this in practice, while at the same time trying to promote efficient matching, is to promote more relevant ads. Suppose that advertiser i ’s relevance is captured by a parameter α_i , so that if ad i is placed in position j it will receive $\alpha_i x_j$ clicks. Then i ’s value for position j is $v_i \alpha_i x_j$, and the efficient assignment ranks advertisers by their impression values $v_i \alpha_i$, rather than their click values. In a weighted GSP auction, the bids are multiplied by the relevance scores and ranked according to $b_i \alpha_i$. The

¹⁷In equilibrium, consumers search sequentially starting with the top position. An interesting feature of their model is advertisers now care about the other ads that appear on the page. Jeziorski and Segal (2009) provide some empirical evidence on consumer behavior that supports the idea that an ad’s click rate depends on the other ads on the page.

weighting allows high quality advertisers to pay less per click for any given position. The resulting GSP equilibria are also efficient, though the revenue may be reduced relative to an unweighted auction.¹⁸ For example, if the high value bidders are also the most clickable, then weighting relaxes the competitive pressure on the winning bidders and lowers prices.¹⁹

An interesting feature of sponsored search that is not captured in the position model is that each search query triggers a new auction, and bidders have the opportunity to frequently update their bids. Why use a real-time market? One reason is that there is variation in the number and type of searches, so advertisers attempting to allocate a budget across keywords will want to optimize dynamically, and prices should be similarly adjusted. An alternative explanation is that bidders are uncertain about their values or quality scores, or the behavior of their competitors, and are continuously updating about these variables. Some recent papers show that the GSP loses some of its appealing properties — for instance, a pure-strategy equilibrium may not exist — when there is uncertainty about bidder values (Gomes and Sweeney, 2009), or residual supply (Hashimoto, 2010). So this raises an empirical question of whether search auctions are in fact relatively stable, and adjust smoothly to variations in demand and supply, or whether real-time bidding introduces some strategic volatility as in the pay-your-bid auctions discussed above.

4.2 Structuring Search in e-Commerce

The matching problem faced by e-commerce sites is similar in many ways to sponsored search, and interacts with both platform pricing and the nature of competition between sellers. At one extreme are cases in which users have identified a specific product (say, a particular make and model of digital camera), and want to find the best price from a reliable seller. A number of papers (e.g. Baye and Morgan, 2000; Baye, Morgan and Scholten,

¹⁸Quality adjustment in the GSP means that advertisers are asked to pay the minimum bid that would ensure their position. So advertiser in position k position pays p_k per click, where $p_k \alpha^{(k)} = b^{(k+1)} \alpha^{(k+1)}$, where $b^{(k)}$ is the bid of the k th-ranked bidder and $\alpha^{(k)}$ her quality score.

¹⁹In a GSP auction with quality weighting the equilibrium payments correspond to market clearing position prices. With no quality weighting, the equilibrium payments correspond to market clearing prices in the market for positions if each position has a price per click rather than a lump-sum price. To see why click-weighting can reduce revenue, suppose bidder 1 has the highest value and click rate, then bidder 2, and so on. The minimum position prices that clear the market are $t_k = \sum_{j \geq k+1} v_j \alpha_j (x_{j-1} - x_j)$. The minimum per-click prices that clear the market are $p_k^* = \sum_{j \geq k+1} v_j (x_{j-1} - x_j) / x_k$, which translates into position payments $t_k^* = \sum_{j \geq k+1} v_j \alpha_k (x_{j-1} - x_j)$. As the qualities α_k are decreasing in k , we have $t_k < t_k^*$.

2004; Ellison and Ellison, 2009) have studied price comparison websites, where retail listings are ranked according to quoted prices, typically with some additional information displayed about shipping costs or seller quality. One insight of this research, which I discuss in the next section, is that sellers have a strong incentive to manipulate or interfere with the search process in order to soften price competition.

A somewhat higher level problem arises when user interests are less specific, or retailers are offering differentiated products. This is the problem faced by platforms such as Amazon, eBay, Alibaba or Taobao, who want to make it easy for buyers to find relevant products, while charging sellers for access to buyers. These platforms frequently rely on a combination of factors to generate listings, including the likely relevance of each seller’s product, prices, and seller quality. eBay is an interesting example, because it initially ordered its search results by auction ending time — prioritizing sales that were about to finish, and giving all sellers an opportunity to be listed first — before moving to a “best match” ranking. With more complex ranking systems, an immediate issue is that the mechanism for assigning priority affects seller incentives. Greater transparency sharpens the incentives, but also expands the scope for inefficient gaming.²⁰ Perhaps in response to this, many platforms appear to use relatively opaque ranking systems.

The organization of consumer search also interacts with the way that platforms structure their prices. For instance, some platforms such as eBay and many job search engines, charge a listing fee. A high listing fee discourages sellers from creating listings that are unlikely to generate sales, reducing the burden on the platform of trying to identify and demote low-quality listings. In contrast, platforms such as Amazon charge a sales commission, which arguably aligns the platform’s incentives with those of sellers. Price comparison engines tend to follow the sponsored search approach and charge sellers per click, although they also may have mechanisms that allow sellers to pay for featured placements. In practice, all of these pricing systems have potential drawbacks in term of aligning incentives. Dellarocas (2009) and Aggarwal, Athey and Yang (2009) discuss some of the problems created by charging sales commissions or payments for “conversions”. Similarly, Hagiu and Jullien (2010) argue

²⁰Examples of gaming can include attempts to manipulate quality or feedback scores, substituting shipping costs for item prices, and various “bait-and-switch”, add-on, or obfuscation strategies.

that many fee structures leave platforms with insufficient incentives to guide consumers toward most likely match. This leads to “search diversion,” in which a platform first steers consumers toward a less likely option, hoping to benefit from a repeat search.

4.3 Matching in Online Advertising

Many internet sites for traditional and social media are at least partly advertising supported. An interesting feature of the advertising markets that support these sites is that online advertising often can be targeted or matched very specifically to individual consumers. While viewers of a television show see the same commercials, viewers of a web page may see different advertisements depending on their demographics or their past internet browsing behavior.²¹ This is an example of the type of customization discussed in Section 2. It also has similarities to the matching problem in sponsored search although the broader advertising market is less structured and the opportunities for advertisers are in many cases less clearly defined.²²

The ability to target advertising in principle allows for more efficient matching, but it also creates some interesting, and relatively unsettled, market design challenges. The reason is that there can be a trade-off between allowing advertisers to flexibility customize their purchases, and imposing a degree of standardization that might lead to a better functioning market. Even in the sponsored search market, where advertisers can bid separately for millions of individual keywords, there is a certain amount of standardization because bids are submitted on a per-click basis that applies to all positions, and in certain cases bids for a particular keyword may be applied to a larger group of similar, but non-identical search queries.

Levin and Milgrom (2010) point out that standardization or “conflation” helps to address at least two problems associated with excessive targeting. One is adverse selection. If certain advertisers are better informed or more sophisticated, allowing them to cherry-pick the best opportunities can make the market unsafe or raise costs for less sophisticated advertisers.

²¹Relatedly, the internet also allows for improved measurement of advertising effectiveness because advertisers can use their targeting ability to run controlled experiments and track the subsequent outcome of advertising exposure. Lewis and Reiley (2010) is an innovative first paper in this area.

²²The organization of display advertising markets is also very different from the sponsored search environment. Display advertising is sold through both negotiated contracts in which publishers guarantee advertisers a fixed number of impressions, and through real-time auction marketplaces.

A second problem is that targeting can lead to thin markets and reduced competition, particularly in contrast to standardized products that conflate, or adjust mechanically for fine distinctions. Bonatti and Bergemann (2010) illustrate this point in an elegant model where increasing the degree of targeting leads advertisers to specialize and lowers seller revenue. McAfee, Papineni, and Vassilvitskii (2010) suggest an innovative way to both protect buyers and create competition in advertising marketplaces by allowing advertisers to buy “representative” bundles, and using automated algorithms to adjust the bundles slightly based on realizations of demand and supply.

5 Competition and Consumer Behavior

The previous section explored the problem of matching buyers to sellers in online markets. In this section, I discuss issues related to competition and consumer behavior in internet markets. I start with the question of how reduced search costs have affected pricing and purchasing behavior. I then discuss the extent to which the internet tends to favor different types of pricing mechanisms than offline markets. Finally, I briefly discuss issues related to reputation and product evaluation in online markets.

5.1 Search Costs and Price Competition

One of the prominent ideas in the early days of online markets was that reduced search costs would intensify competition and reduce or even eliminate price dispersion. This prediction has generated a significant body of empirical work, and more recently, some new theory. An early study by Brynjolfsson and Smith (2000) looked at the prices of books and CDs, concluding that online prices were roughly ten percent lower, but featured significant variation across retailers, up to 30% of the average price. Baye, Morgan and Scholten (2004) used a larger and more systematic dataset from a price comparison engine to study consumer electronics. In their data, price differences in markets with just a few sellers were around 20%. In markets with many sellers (e.g. over a dozen), the gap between the top few prices was relatively narrow, although the spread between the highest and the lowest price remained over 30%. They frame the results in terms of Baye and Morgan’s (2001) model of price search. In

Baye and Morgan’s model, retailers set a single price that applies on the comparison engine and for consumers who come directly to the retailer’s website. Some “direct” shoppers do not check other prices, leading to equilibrium price dispersion.

Ellison and Ellison’s (2009) study of price comparison engines is noteworthy because they combine data from the comparison site with proprietary data from a large seller that allows them to see how listing position relates to sales volume.²³ They find that the returns to being the low price seller are very high, because demand falls off sharply with a seller’s position. This leads to intense competition to state low prices, at least for low-quality products. It also gives sellers an incentive to use various “loss leader” or “bait and switch” tactics that divert consumers who have clicked on listing toward products with higher margins. Ellison (2005) provides a theoretical model which captures the idea that add-ons can soften price competition, while Ellison and Wolinsky (2009) study a more traditional model in which firms soften competition by “obfuscating” and increasing consumer search costs.

In the models just described, consumers find it costly to search, but their search behavior is sophisticated. A number of recent papers argue that a lack of consumer sophistication helps to explain various features of online pricing and competition. For example, Hossain and Morgan (2006), and Brown, Hossain and Morgan (2009) investigate whether consumers on eBay place the same weight on price and shipping fee. They find that in certain cases auction prices do not fully compensate for differences in shipping fees. Lee and Malmendier (2010) is another behavioral paper that focuses on eBay. They study an episode in which a particular board game was simultaneously offered at a posted price and by auction. Although the average auction price was quite similar to the posted price, the game sold for \$10 or more above the posted price in about a quarter of the auctions. Based on this finding, they argue that at least some buyers engage in insufficient search.

These studies mainly focus on consumer demand for individual goods. There is also a related question of whether reducing search costs re-allocates demand across products. Some influential early papers argued that lower search and display costs online would shift demand toward so-called “tail” products. For instance, Brynjolffson, Hu and Smith (2003)

²³Ghose and Yao (2009) point out that one limitation with most studies of price comparison engines is that they look for dispersion in posted prices, rather than in transaction prices. They provide evidence from the GAO’s procurement marketplace, showing that transaction prices feature much lower dispersion.

estimated that of the roughly two million book titles offered by Amazon, the top 100,000 — which would be roughly the number of titles available at a Barnes and Noble superstore — accounted for only about 70% of total sales (see also Chevalier and Goolsbee, 2003). While the proliferation of products online seems hard to debate, the “long tail” effect is less obvious. One reason is that if a certain product become successful in a certain market, the internet offers an opportunity to expand rapidly. Elberse and Olberhozer-Gee (2008) argue that online markets have the reverse effect of channeling demand toward “superstar” products, and provide some evidence of this from the video rental business. Given the wealth of data available about online purchasing decisions, this debate seems ripe for further empirical analysis.

5.2 Auctions and Posted Prices

Another influential idea in the early days of internet markets was that lower transaction costs would facilitate the use of dynamic pricing mechanisms such as auctions (Reiley, 2001; Hall, 2002; Bajari and Hortacsu, 2004). Generally speaking, auctions have the virtue that they encourage buyer competition for scarce goods and facilitate price discovery. But they tend to involve higher transaction costs than posted prices because a seller has to assemble and coordinate competing buyers to run an auction. Internet auction platforms such as eBay reduce these costs by allowing bidders to bid remotely using a proxy mechanism.²⁴ But because the internet also reduces the cost of finding prices for comparable items, it seems possible that it would also reduce the need for price discovery. Einav, Knoepfle, Kuchler and Levin (in progress) note that in the eBay marketplace, which was once dominated by ascending auctions, posted prices constitute around 80% of current listings.

To see how the trade-off between pricing mechanisms might work, consider a seller with a single item and a cost of selling equal to c . Suppose there is a set of buyers who have identical value v for the seller’s item. The seller is uncertain about the value buyers assign to the object, and views it as a random variable. For concreteness, let’s assume a uniform

²⁴Many studies have pointed out that even though eBay’s auctions are technically ascending often, bids often come in close to the end, so that in practice they can sometimes be more similar to second-price sealed bidding (e.g. Bajari and Hortacsu, 2003, 2004; Roth and Ockenfels, 2002).

distribution on $[0,1]$. Now imagine that the seller can either post a price p , or run an auction with some reserve price r . The drawback to running an auction is that it inconveniences buyers, an effect we can capture in shorthand by assuming their value is reduced by an amount ϕ . Now, if the seller sets a price p , the item will sell if $v \geq p$, or with probability $1 - p$. If instead the seller runs an auction with reserve price r , the item will sell if $v - \phi \geq r$, and if it does sell, competition between buyers will drive the price to $v - \phi$.

In this very simple model, an auction provides an effective means to sell with high probability (by setting a low reserve price) while ensuring buyer competition and price discovery. On the other hand, the higher transaction cost makes it a less desirable way to maintain a relatively high price.²⁵ This is illustrated in Figure 3, which shows the “price-quantity” pairs that are attainable through different choices of posted price p or reserve price r (plotted assuming that $c = \phi = 1/3$).²⁶ Einav et al. provide evidence on the listing choices of eBay sellers, and the resulting sale outcomes, that is consistent with this trade-off and some of its implications, such as the idea that posted prices should become more attractive when sellers have thinner margins, or less uncertainty about buyer valuations. They argue that the trade-off between price discovery and transaction costs also helps to explain why eBay’s market transitioned from auctions to posted prices as the market matured.

For certain types of goods, auctions can play a role in allocating last-minute or remnant inventory. Sweeting (2010) provides an interesting example in studying the market for baseball tickets on StubHub and eBay. He first shows that prices adjust downward as the game approaches, and relates this to the predictions of dynamic pricing models. In many such models, the opportunity cost of selling a perishable good falls as the “expiration date” approaches, leading to falling prices. Of course, this prediction can depend on whether buyers anticipate price declines and time their purchases strategically. Board and Skrzypacz (2010) show how the optimal sales strategy for a perishable goods seller with strategic buyers can involve dynamic price adjustment followed by a last-minute auction. This pattern is at least qualitatively consistent with internet sites conducting “last-minute” auctions for plane and

²⁵The qualitative point is not specific to the numerical example, although in general it relies on the distribution of consumer values being log-concave.

²⁶The figure also show the optimal posted price $p^* = (1 + c) / 2$, which results in profit $\pi_P = (1 - c)^2 / 4$, and the optimal auction reserve price is $r^* = c$, which leads to expected profit $\pi_A = (1 - c - \phi)^2 / 2$. For the parameters in Figure 3, both mechanisms have the same maximum profit, equal to $1/18$.

hotel reservations, and with a finding of Sweeting that baseball tickets are increasingly sold by auction close to game day.²⁷

5.3 Reputation and Evaluation Mechanisms

A characteristic feature of online markets is that buyers typically cannot inspect goods, which creates opportunities for misrepresentation and even outright fraud. A nice illustration of this is provided by Jin and Kato (2006), who purchased ungraded baseball cards both online and offline and found that the cards purchased online, though advertised similarly, were substantially lower quality when they were subsequently graded. Problems of misrepresentation can become more acute as marketplaces expand, and there is perhaps less repeat trade. Platforms frequently try to address these issues either through some process of certification, or through a reputation feedback system that elicits information from users and then aggregates and displays the information to others.²⁸ There is now a substantial body of research on this topic, which is surveyed by Dellarocas (2006).

Many studies, starting with Resnick and Zeckhauser (2001), have looked at eBay's reputation system, generally finding that sellers with higher feedback scores enjoy some modest benefits. A typical concern in these studies is that the feedback users give is overwhelmingly positive. Bolton, Greiner and Ockenfels (2009) address the last point by focusing on the design of eBay's system. They point out that eBay's original mechanism suffered from a severe incentive problem. Because sellers could retaliate after receiving negative feedback, there was little reason for buyers to ever give negative reviews. Bolton et al. use laboratory experiments to demonstrate how the incentives for honest reporting can be dulled by retaliation, and show that eBay's decision to eliminate seller feedback led to more informative reports.

²⁷Another example of where online markets have fostered innovation in pricing is in financial trading. A common issue in real-time financial markets is that at any given time there is limited demand and supply, so a large order can have a substantial price impact. Moreover, strategic traders can take advantage of this by "front-running" or trading ahead of a large order. As a result, traders can be hesitant to place large orders in an electronic order book, or may spend considerable resources trying to break up or time the order. In the last few years, however, competition between electronic trading platforms has led to considerable innovation so that exchanges are beginning to allow orders that are partially concealed, or bundled orders (Macri-Lassus, 2010).

²⁸Lewis (2010) also provides evidence on the use of seller disclosure strategies to reduce problems of asymmetric information in the online sale of used cars.

The design of systems to aggregate user reviews or product evaluations is closely related to the design of reputation mechanisms. Avery, Resnick and Zeckhauser (2001) is an early study of recommender systems that focuses on how to structure the timing of evaluations and payments to consumers. Many of the mechanisms currently in use on platforms such as Netflix or Amazon or consumer review sites do not use payments, although users perhaps enjoy status benefits from posting informative evaluations. The design and incentives of these systems, and their effects on consumer purchasing patterns, have not received that much attention from economists, although they have been active topics of research in both computer science and marketing.

6 Conclusion

This paper has discussed the economics of internet markets and some of the research on this topic from the last decade. The development of these markets has offered an exciting opportunity to study how changes in technology affect economic activity and the efficient organization of markets. Many internet markets also provide novel environments for applying and testing economic theories about platform competition and market design, and for analyzing competition and consumer behavior in relatively structured, controlled environments with extraordinarily detailed data. Though the pace may not match the growth rates I referred to at the beginning of this essay, I expect to see many more research advances in this area over the next decade.

References

- Acquisti, Alessandro and Ralph Gross, "Predicting Social Security Numbers from Public Data," *Proceedings of the National Academy of Sciences*, 2009, 106(27), pp. 10975-10980.
- Aggarwal, Nikhil, Susan Athey and David Yang, "Skewed Bidding in Pay-per-Action Auctions for Online Advertising," *American Economic Review*, 2009, 99(2), pp. 441-447.
- Armstrong, Mark, "Competition in Two-Sided Markets," *Rand Journal of Economics*, 37(3), Autumn 2006, pp. 668-691.
- Athey, Susan and Glenn Ellison, "Position Auctions with Consumer Search," MIT Working Paper, 2008.
- Athey, Susan and Denis Nekipelov, "A Structural Model of Sponsored Search Auctions," UC Berkeley Working Paper, 2010
- Avery, Christopher, Paul Resnick and Richard Zeckhauser, "The Market for Evaluations," *American Economic Review*, 89(3), September 1999, pp. 564-584.
- Bajari, Patrick and Ali Hortacsu, "Winner's Curse, Reserve Prices and Endogenous Entry: Empirical Insights from eBay Auctions," *Rand Journal of Economics*, 34(2), Summer 2003.
- Bajari, Patrick and Ali Hortacsu, "Economic Insights from Internet Auctions," *Journal of Economic Literature*, 42(2), June 2004, pp. 457-486.
- Baye, Michael R. and John Morgan, "Information Gatekeepers on the Internet and the Competitiveness of Homogeneous Product Markets," *American Economic Review*, 91(3), June 2001, pp. 454-474.
- Baye, Michael R., John Morgan and Patrick Scholten, "Price Dispersion in the Large and in the Small: Evidence from an Internet Price Comparison Site," *Journal of Industrial Economics*, 52(4), December 2004, pp. 463-96.
- Board, Simon and Andy Skrzypacz, "Optimal Dynamic Auctions for Durable Goods: Posted Prices and Fire-sales," Stanford University Working Paper, 2010.
- Bolton, Gary, Ben Greiner and Axel Ockenfels, "Engineering Trust: Strategic Behavior and the Production of Reputation Information," University of Indiana Working Paper, 2008.
- Bonatti, Alessandro and Dirk Bergemann, "Targeting in Advertising Markets: Implications for Offline vs. Online Media," Yale University Working Paper, 2010.
- Borgers, Tilman, Ingemar Cox, Martin Pesendorfer, and Vaclav Petricek, "Equilibrium Bids in Auctions of Sponsored Links: Theory and Evidence," University of Michigan, 2008.

- Brown, Jennifer, Tanjim Hossain and John Morgan, "Shrouded Attributes and Information Suppression: Evidence from Field Experiments," *Quarterly Journal of Economics*, 2010.
- Brown, Jennifer and John Morgan, "How much is a Dollar Worth? Tipping versus Equilibrium Coexistence on Competing Online Auction Sites," *Journal of Political Economy*, 2009, 117(4), pp. 668-700.
- Brynjolfsson, Erik and Michael D. Smith, "Frictionless Commerce? A Comparison of Internet and Conventional Retailers," *Management Science*, 46(4), April 2000, pp. 563-585.
- Brynjolfsson, Erik, Yu (Jeffrey) Hu, and Michael D. Smith, "Consumer Surplus in the Digital Economy: Estimating the Value of Increased Product Variety at Online Booksellers," *Management Science*, 49(11), November 2003, pp. 1580-1596.
- Bulow, Jeremy and Jonathan Levin, "Matching and Price Competition," *American Economic Review*, 96(3), June 2006, pp. 652-668.
- Caillaud, Bernard and Bruno Jullien, "Chicken and Egg: Competition between Intermediation Service Providers," *Rand Journal of Economics*, 2003, 34, pp. 309-328.
- Chen, Yongmin and Chuan He, "Paid Placemenet: Advertising and Search on the Internet," NET Institute Working Paper, September 2006.
- Chevalier, Judy and Austan Goolsbee, "Measuring Prices and Price Competition Online: Amazon vs. Barnes and Noble," *Quantitative Marketing and Economics*, 2, June 2003.
- de Los Santos, Babur, Ali Hortacsu and Matthijs Widenbeest, "Testing Models of Consumer Behavior Using Data on Web Browsing and Purchasing Behavior," University of Chicago Working Paper, 2009.
- Dellarocas, Chrysanthos, "Reputation Mechanisms," *Handbook of Economics and Information Systems*, Terence Hendershott, ed., Elsevier Publishing, 2006.
- Dellarocas, Chrysanthos, "Double Marginalization in Performance-Based Advertising: Implications and Solutions," Boston University Working Paper, 2010.
- Douglas, Jason, Ali Hortacsu, and Asis Martinez-Jerez, "The Geography of Trade on eBay and MercadoLibre," *American Economic Journal: Microeconomics*, 1(1), February 2009, pp. 53-74.
- Edelman, Benjamin, Michael Ostrovsky and Michael Schwarz, "Internet Advertising and the Generalized Second Price Auction: Selling Billions of Dollars Worth of Keywords," *American Economic Review*, 97(1), March 2007, pp. 242-259.
- Edelman, Benjamin and Michael Ostrovsky, "Strategic Bidder Behavior in Sponsored Search Auctions," *Decision Support Systems*, 43(1), February 2007, pp. 192-198.
- Einav, Liran, Dan Knoepfle, Theresa Kuchler and Jonathan Levin, "Auctions and Posted Prices in Online Markets," in progress.

- Ellison, Glenn, "A Model of Add-On Pricing," *Quarterly Journal of Economics*, 120(2), May 2005, pp. 585-637.
- Ellison, Glenn and Sara Fisher Ellison, "Lessons from the Internet," *Journal of Economic Perspectives*, 19(2), Spring 2005, pp. 139-158.
- Ellison, Glenn and Sara Fisher Ellison, "Search, Obfuscation and Price Elasticities on the Internet," *Econometrica*, 77(2), March 2009, pp. 427-452.
- Ellison, Glenn and Drew Fudenberg, "Knife-Edge or Plateau: When Do Market Models Tip?" *Quarterly Journal of Economics*, 2003, 118(4), pp. 1249-1278.
- Ellison, Glenn and Alexander Wolitsky, "A Search Cost Model of Obfuscation," MIT Working Paper, 2009.
- Evans, David, Andre Hagiu and Richard Schmalensee, *Invisible Engines: How Software Platforms Drive Innovation and Transform Industries*, MIT Press, 2006.
- Farrell, Joseph and Paul Klemperer, "Coordination and Lock-In: Competition with Switching Costs and Network Effects," *Handbook of Industrial Organization, Volume 3*, ed. Mark Armstrong and Robert Porter, Excelsvier, 2007.
- Ghose, Anindya and Yuliang Yao, "Using Transaction Prices to Re-Examine Price Dispersion in Electronic Markets," *Information Systems Research*, forthcoming.
- Gomes, Renato, "Mechanism Design in Two-Sided Markets: Auctioning Users," Northwestern University Working Paper, 2009.
- Gomes, Renato and Kane Sweeney, "Bayes-Nash Equilibria of the Generalized Second Price Auction," Northwestern University Working Paper, 2009.
- Hagiu, Andrei and Bruno Julien, "Why Do Intermediaries Divert Search?" Harvard Business School Working Paper, 2010.
- Hall, Robert E., *Digital Dealing: How e-Markets are Transforming the Economy*, W.W. Norton and Company, 2002.
- Hitsch, Gunter, Ali Hortacsu and Dan Ariely, "Matching and Sorting in Online Dating," *American Economic Review*, 100(1), March 2010, pp. 130-163.
- Jeziorski, Przemyslaw and Ilya Segal, "What Makes them Click: Empirical Analysis of Consumer Demand for Internet Search Advertising," Stanford University Working Paper, February 2009.
- Jin, Ginger Zhe and Andrew Kato, "Dividing Online and Offline: A Case Study," *Review of Economic Studies*, 74(3), June 2007, pp. 981-1004.
- Kroft, Kory and Devin G. Pope, "Does Online Search Crowd Out Traditional Search and Improve Matching Efficiency? Evidence from Craigslist," University of Pennsylvania Working Paper, 2008.

- Lee, Young Han and Ulrike Malmendier, "The Bidder's Curse," *American Economic Review*, forthcoming.
- Levin, Jonathan and Paul Milgrom, "Online Advertising: Heterogeneity and Conflation in Market Design," *American Economic Review*, 100(2), May 2010.
- Lewis, Greg, "Asymmetric Information, Adverse Selection and Online Disclosure: the Case of eBay Motors," Harvard University Working Paper, 2010.
- Lewis, Randall and David Reiley, "Retail Advertising Works! Measuring the Effects of Advertising on Sales via a Controlled Experiment on Yahoo!," Yahoo! Research Working Paper, 2009.
- Lucking-Reiley, David "Auctions on the Internet: What's Being Auctioned, and How?" *Journal of Industrial Economics*, 48(3), September 2000, pp. 227-252.
- Malmendier, Ulrike and Adam Szeidl, "Fishing for Fools," U.C. Berkeley Working Paper, 2008.
- McAfee, R. Preston, Kishore Papineni, and Sergei Vassilvitskii, "Maximally Representative Allocations for Guaranteed Delivery Advertising Campaigns," Yahoo! Research Working Paper, 2010.
- Milgrom, Paul, "Simplified Mechanisms, with an Application to Sponsored Search Auctions," *Games and Economic Behavior*, forthcoming.
- Ostrovsky, Michael and Michael Schwarz, "Reserve Prices in Internet Advertising Auctions: A Field Experiment," Stanford University Working Paper, 2009.
- Resnick, Paul, Richard Zeckhauser, E. Friedman and K. Kuwabara, "Reputation Systems," *Communications of the ACM*, 43(12), pp. 45-48.
- Rochet, Jean-Charles and Jean Tirole, "Platform Competition in Two-Sided Markets," *Journal of the European Economic Association*, 1(4), June 2003, pp. 990-1029.
- Rochet, Jean-Charles and Jean Tirole, "Two-Sided Markets: A Progress Report" *Rand Journal of Economics*, 37(3), Autumn 2006, pp. 645-667.
- Roth, Alvin and Axel Ockenfels, "Last Minute Bidding and the Rules for Ending Second-Price Auctions: Evidence from eBay and Amazon Auctions on the Internet," *American Economic Review*, 92(4), September 2002, pp. 1093-1103.
- Rysman, Marc, "The Economics of Two-Sided Markets," *Journal of Economic Perspectives*, 23(3), Summer 2009, pp. 125-143.
- Segal, Ilya, "Contracting with Externalities," *Quarterly Journal of Economics*, 114(2), May 1999, pp. 337-388.
- Sweeting, Andrew, "Price Dynamics in Perishable Goods Markets: The Case of Secondary Markets for Major League Baseball Tickets," Duke University Working Paper, 2009.

- Varian, Hal, "Position Auctions," *International Journal of Industrial Organization*, 25(6), December 2007, pp. 1163-1178.
- Varian, Hal, "Online Ad Auctions," *American Economic Review*, 99(2), May 2009, pp. 430-434.
- Varian, Hal, "Computer-Mediated Exchange," *American Economic Review*, 100(2), May 2010.
- Weyl, E. Glen, "A Price Theory of Multi-Sided Platforms," *American Economic Review*, forthcoming.

Figure 1: Estimated Cost of Selected Keywords

(a) Auto Insurance

(b) Mesothelioma

(c) VOIP Phone

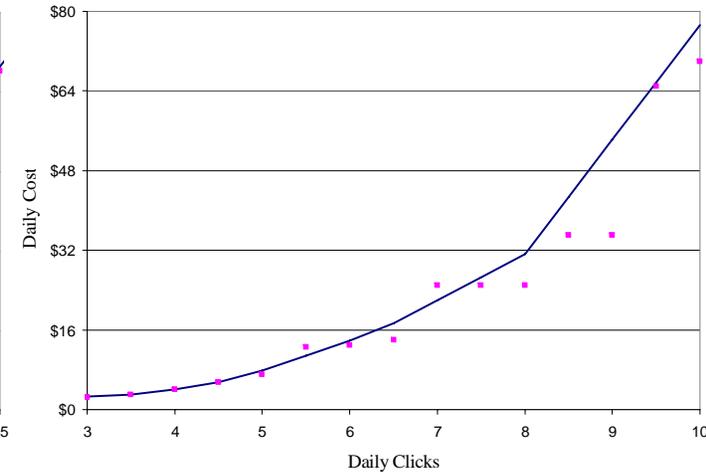
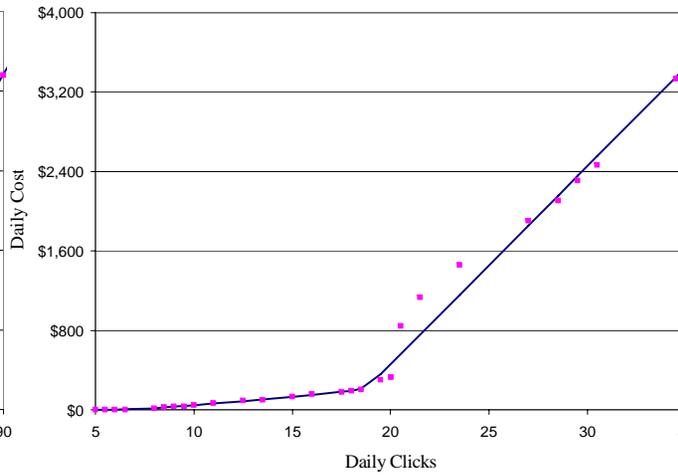
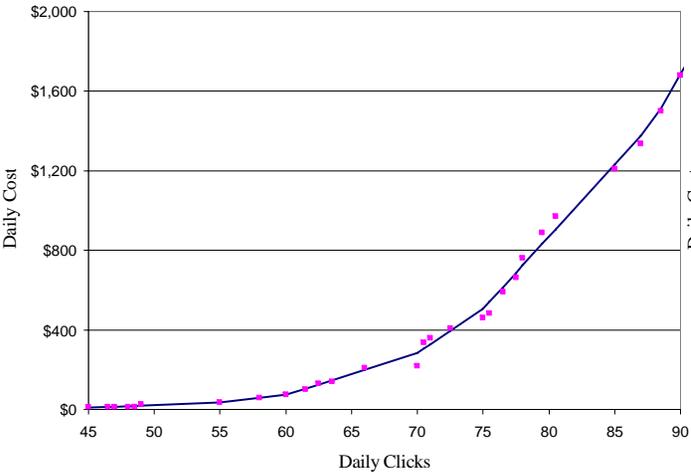
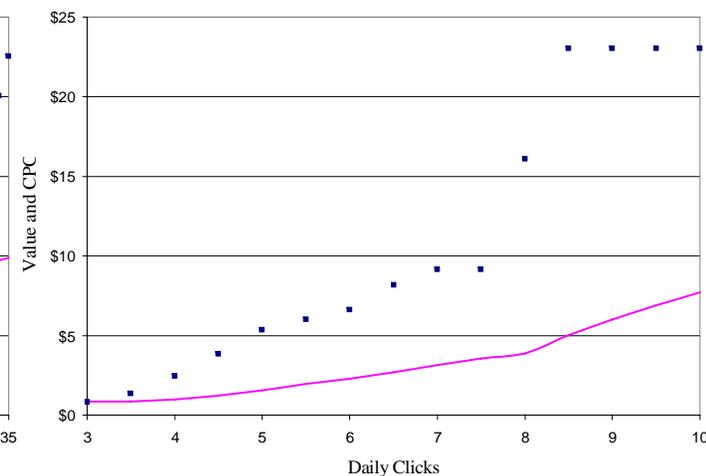
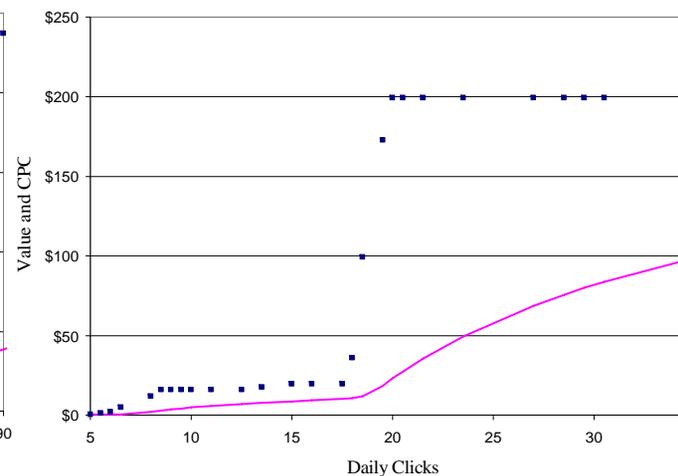
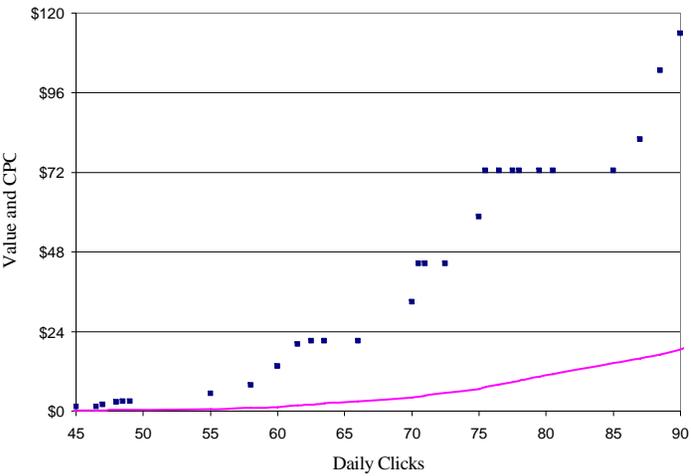


Figure 2: Estimated Cost per Click and Implied Value per Click

(a) Auto Insurance

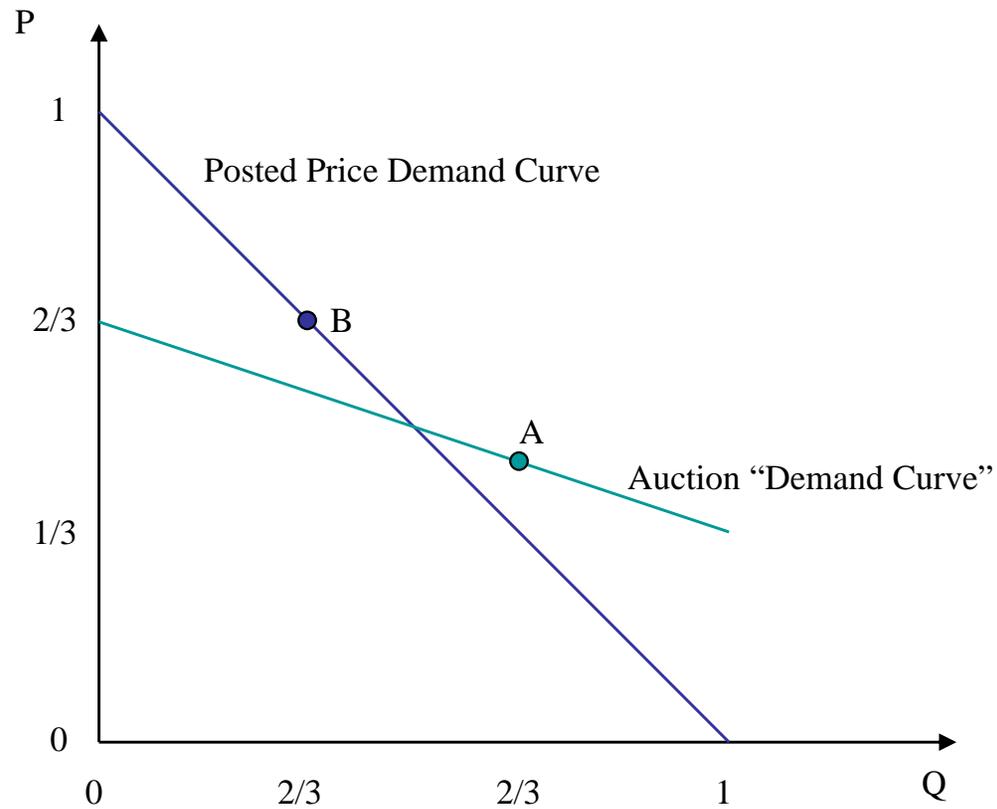
(b) Mesothelioma

(c) VOIP Phone



Notes: Figure 1 shows estimated clicks and cost per day for selected keywords from Google's Traffic Estimator, accessed in May 2010. The fitted curves in are the piecewise linear convex curves that minimize the sum of squared deviations from the data. Figure 2 shows the cost per click for each quantity, $c(x)/x$, and the implied value, $v=c'(x)$, for a bidder purchasing that number of clicks, both obtained from the fitted cost curve $c(x)$ in Figure 1.

Figure 3: "Price-Quantity" Pairs for Auctions and Posted Prices



Notes: Figure shows the market demand curve for a posted price seller, and a plot of probability of sale against expected price for auctions with different reserve prices. Point A results from an optimal auction, and B from an optimal posted price.