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How do firms make money selling digital goods online?

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Abstract We review research on revenue models used by online firms who offer digital goods. Such goods are non-rival, have near zero marginal cost of production and distribution, low marginal cost of consumer search, and low transaction costs. Additionally, firms can easily observe and measure consumer behavior. We start by asking what consumers can offer in exchange for digital goods. We suggest that consumers can offer their money, personal information, or time. Firms, in turn, can generate revenue by selling digital content, brokering consumer information, or

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showing advertising. We discuss the firm's trade-off in choosing between the different revenue streams, such as offering paid content or free content while relying on advertising revenues. We then turn to specific challenges firms face when choosing a revenue model based on either content, information, or advertising. Additionally, we discuss nascent revenue models that combine different revenue streams such as crowdfunding (content and information) or blogs (information and advertising). We conclude with a discussion of opportunities for future research including implications for firms' revenue models from the increasing importance of the mobile Internet.

Keywords Internet · Digital goods · Online advertising · Revenue model · Paywall · Paid content · Crowdfunding · Pricing · Privacy

1 Introduction

For digital products delivered online, many firms can charge customers for access to content, sell information about their customers, or sell their customers' attention in the form of online advertising.[1] Firms can also combine multiple revenue streams, for example, charge customers for a subset of services and generate additional revenues from selling advertising or information. For example, to monetize news online (e.g., nytimes.com), firms have long focused on advertising revenues but are increasingly offering subscriptions. Revenue models for music and movies (e.g., iTunes, Pandora, YouTube, Netflix) range from selling song-by-song to ad-supported and paid streaming. E-books (e.g., Kindle, OverDrive) are sold by the book or rented. Providers of games (e.g., Zynga, World of Warcraft) rely on a wide range of revenue models including in-app purchases, subscription, ads, and purchase, whereas software as a service (e.g., Dropbox) is offered by subscription or one-off purchase.

The ability to select among revenue streams has broadened and complicated a decision previously restricted to pricing. First, for many firms, the choice between revenue models involves trade-offs that arise because increasing revenue from one source (e.g., subscription) most often reduces revenue from an alternative source (e.g., advertising or the sale of user information). Second, optimally designing each revenue stream is complex. A firm that charges for access to services needs to determine optimal prices, involving the choice of selling vs. renting or charging subscriptions vs. micropayments. A firm aiming to sell information about its customer base has to decide which information to sell at what price. A firm that aims to generate online advertising revenues faces major challenges regarding measuring the effectiveness of advertising, optimally targeting customers, and understanding the effect of ad content on customer behavior.

Establishing the best revenue and pricing model requires an understanding of what is different about the digital product under consideration. Digital products present a unique combination of traits: (1) they are non-rival, meaning consumption of the good

[1] We focus on revenue models for digital products, abstracting from settings where the internet is used merely to communicate or sell physical products. By "online," we mean using digital communication channels. Because these are digital products, "online firms" refers to those firms that communicate with, and sell to, consumers using digital communication, typically through the internet.

does not decrease its availability to others, (2) they have near zero marginal cost of production and distribution even over large distances, (3) they have lower marginal cost of search than products sold in physical (offline) stores, and (4) they have lower transaction cost than non-digital products. Additionally, in digital environments, firms can relatively easily observe and measure detailed consumer behavior (Shapiro and Varian 1998).

These features of the basic economics of digital goods suggest the strengths and weaknesses of various online revenue models. The challenge of choosing the best revenue model online has inspired intensive research in marketing, economics, and information systems. The next section aims to give an overview of current research on online revenue models. We then point to future directions for research.

2 Choice of revenue model

We propose that the firm has three ways of generating revenues online. First, the firm can sell content, or more broadly services, to consumers. Second, the firm can sell information about consumers (for example, in the form of cookies). Third, the firm can sell space to advertisers. This classification is based on the fact that in exchange for access to a digital good, consumers can offer money, information (such as personal data), or time (often in the form of attention). We next discuss the firm's decision problem of selecting or combining revenue streams before turning to challenges related to the implementation of specific revenue models.

2.1 Which way to go: content, information, or advertising?

Research on a firm's choice of revenue streams has largely focused on the choice between content and advertising. Here, the basic trade-off is that moving from an advertising-only revenue model to charging for content will reduce viewership and thus hurt advertising revenues. Recent analytical research points out that greater competitive intensity may increase profits from charging for content and decrease profits from advertising (Godes et al. 2009). An alternative view focuses on the effect of consumer heterogeneity in their willingness to pay to avoid ads and concludes that it is often best to receive both advertising and content revenue (Prasad et al. 2003). Additional work has focused on free units as a sample of the paid product, demonstrating that free (digital) goods can increase long-term sales (Bawa and Shoemaker 2004; Boom 2010) but that sampling enhances subscription demand only for intermediate levels of advertising effectiveness (Halbheer et al. 2013).

Recent empirical research has made some advances in analyzing the firm's trade-off between content and advertising revenues. Pauwels and Weiss (2007) show for an online content provider targeted towards marketing professionals that moving from free to fee can be profitable, despite loss of advertising revenue. Yet, Chiou and Tucker (2012) find that visits to an online news site fall significantly after the introduction of a paywall, particularly among younger consumers. Lambrecht and Misra (2013) empirically look at the trade-off between content (subscription) and advertising. They document that subscription reduces views and advertising revenues and quantify this trade-off. They also find that as a result of heterogeneity in willingness to pay over consumers and time, a static model may be suboptimal. Instead, firms can increase revenue by flexibly adjusting the amount of paid content they offer over time.

We know less about the balance between advertising revenues and revenues from selling information, suggesting an avenue for future research.

2.2 Content: selling the service

The first sale doctrine permits anyone who owns an original copy of a physical product to rent or resell it as they choose. Reselling or renting digital products is particularly attractive since such goods are non-rival when there is no regulation or technology preventing people from sharing. But it is almost impossible to resell or rent a digital product without first making a copy which would result in copyright infringement.[2] To prevent consumers from copying, firms create locks through digital rights management, circumvention of which is prohibited by the Digital Millennium Copyright Act. With legal resale markets shut down, firms need to rethink their pricing model.

Interestingly, many firms use rigid pricing structures across time and content, mainly for user-friendliness. While most songs on Apple's iTunes store are priced at $1.29 and new standard definition movies are priced at $14.99/$3.99 for purchase/rent, content providers demand more flexibly priced content and want to adjust prices over time. However, Rao (2013) points out that these rigid pricing structures resemble price commitment and can benefit content providers by providing them with a credible commitment device. But when unable to commit to a price path, a firm should serve both purchase and rental markets because the purchase option enables indirect price discrimination. Unlike the classical (Coase conjecture) durable goods problem of time-inconsistency, she finds that when consumers place a premium on accessing new content they are less likely to wait for cheaper prices which increases the firm's pricing power.

Additional questions relating to the design of a content-based business model include the design of pricing tiers, duration of subscription plans, and the design of freemium models. Under which circumstances, should firms charge subscriptions for unlimited access over a fixed period of time versus alternatively offering pricing plans with a limited allowance of free usage, thereafter charging per unit of use (Lambrecht et al. 2007)? Should a firm charge for subscriptions annually, monthly, or even daily (Gourville 1998)? Alternatively, when should firms rely on payments for each individual download or interaction? Digital technology has enabled the possibility of "micropayments" or payments of very small amounts that typically would not be possible using standard credit card network access fees. But as Athey et al. (2013) point out, micropayments and subscriptions may affect consumer behavior differently and thus alter a firm's trade-off between revenues from content and advertising. In initial research on the design of a freemium model, Lee et al. (working paper) ask how much value a free version should provide relative to the premium version of the product that consumers pay for. We encourage further research into consumer response to

[2] Despite regulatory efforts and technological advances, piracy of digital content remains an issue. There is currently no academic consensus on whether piracy hurts sales. Liebowitz (2004) and Waldfogel (2010) find evidence that piracy hurts sales, while Blackburn (2004) and Oberholzer-Gee and Strumpf (2007) find no substantial effect. In the case of concert tickets, Mortimer et al. (2012) showed that music piracy likely helped the sale of complementary goods.

different methods and frequencies of payments as well as to the design of content offerings that charge different prices for different tiers of access.

2.3 Information: selling data

Personal data, typically consisting of consumers' identities, habits, needs, and/or preferences, can be sold online in several ways. Data sales constitute an auxiliary revenue source for specific websites that supply information about users' activity to direct marketing companies. In addition, websites can partner with data management platforms—aggregators that place cookies on users' computers and collect information reflecting their most recent online activity.[3] Finally, data can be sold indirectly through bundling of information and services such as targeted advertising or matchmaking services such as crowdfunding.

Bergemann and Bonatti (2013) study the direct sale of consumer-level information by a monopolist data management platform. They develop a matching model where firms can reach a population of heterogeneous consumers through targeted advertising. In order to maximize profits, firms would like to advertise more (less) aggressively to consumers with a high (low) valuation for their product. However, neither advertisers nor web publishers, as the sellers of ad space, own the information necessary to tailor ad spending to the characteristics of individual consumers. A data provider monetizes the data's matchmaking potential by selling user information about each consumer to advertisers.

There are two key features of the model: First, information about each consumer is sold separately and second, individual queries to the database are priced linearly. These features distinguish the cookies-sale model from other frameworks for selling information, such as Sarvary and Parker (1997), Iyer and Soberman (2000), and Xiang and Sarvary (2013), which consider the sale of noisy signals about a variable of interest. Under this pricing model, each advertiser acquires detailed information about a *targeted set* of consumers and can perfectly tailor ad spending to their characteristics. At the same time, each advertiser is uninformed about a large *residual set* of consumers and must form an expectation of their value. Moreover, the composition of the targeted set influences the value of advertising to the residual set through the advertiser's inference about the residual consumers' valuations. In other words, there is value for each advertiser in the complement of the information being purchased (e.g., information on all consumers who purchased a car implicitly includes the information on who did not purchase), suggesting there might be value to "negative targeting" as well as "positive targeting." Several studies point indirectly to the attractiveness of a negative-targeting strategy. See, for example, the contexts described by Blake et al. (2013) and by Anderson and Simester (2013).

The above discussion takes as given the current structure of cookies as an industry-wide standard way of tracking customers. It is possible that proprietary tracking techniques that are distinct from cookies may gain prominence. For example, Google or Apple might use their own tracking technology that exploits unique user IDs. Currently, we have little understanding of how such proprietary technologies might

[3] For detailed report on "The State of Data Collection on the Web," see the 2013 Krux Cross Industry Study at http://www.krux.com/pro/broadcasts/krux_research/CIS2013/.

affect the market structure for firms that buy and sell information. We see this as a promising area for future work.

2.4 Advertising: selling eyeballs

Most of the Web's popular destinations, such as Google, Facebook, and YouTube, rely on advertising income, which comes mostly from search ads (links shown alongside results from queries typed into search engines) or display ads (images or animations shown next to web content).

Advertising effectiveness is difficult to measure both offline (Lewis and Reiley 2014; Lewis et al. 2013) and online (Lewis and Rao 2013) since advertising's effects, while potentially economically large, can be small relative to the baseline noise of volatile or sparse transactions.

This statistical problem implies that Web publishers have difficulty demonstrating to advertisers that ads have a profitable impact. Blake et al. (2013) demonstrate for ads placed by eBay that traditional ways of measuring advertising effectiveness were confounded by selection bias common in Internet applications. This "activity bias" (Lewis et al. 2011) led the advertiser to believe that their advertising was significantly more effective than the researchers' experiments indicate.

The recent ability to monitor detailed consumer behavior and to combine such data with a variety of data sources, including online surveys, creditworthiness, and geolocation, has the potential to improve accountability, ad targeting, and ultimately, advertising effectiveness (Johnson et al. 2013).[4] Retargeted advertising is a recent example of such a combination of information that likewise decreases baseline noise. It allows firms to focus on consumers who have shown prior interest in the firm's offering and combines the knowledge of what product a consumer viewed in a store with data on their browsing behavior on the web (Lambrecht and Tucker 2013).

More broadly, new technologies facilitate natural and field experiments that cleanly measure advertising effectiveness. Using such technologies, Lambrecht and Tucker (2013) provide a comparative analysis of retargeting creative content. Sahni (2013a) shows that online banner ad displays increase advertiser's current and future sales among individuals searching on a restaurant search website. The paper likewise quantifies the long-term effects of temporal spacing between ads. Lewis and Reiley (2014) and Lewis et al. (2013) demonstrate that online display advertising can influence customers' purchasing behavior online and in stores. Ghose et al. (2013b) examine Internet and mobile ads and how they interact. Lewis and Nguyen (2013) examine display ad campaigns that vary targeting and banner shape. They find heterogeneity in effectiveness and gains in statistical power by using additional data available in digital advertising to restrict the sample of outcomes they analyze. Additional studies demonstrate that the marginal effect of display advertising only weakly declines in the number of impressions (Johnson et al. 2013; Lewis 2010) and explore the effectiveness of targeting early trend adopters on Twitter (Lambrecht et al. 2014).

[4] The increased use and monetization of detailed customer-level data through the sale of information and advertising has led to greater demands for privacy regulations since consumers often show great discomfort with privacy violations (John et al. 2011). But privacy also affects advertising effectiveness. Goldfarb and Tucker (2011a, b) show that advertising is less effective when privacy policy is strict.

The Internet's scale furthermore allows researchers to measure subtle effects of economic importance. For example, advertising may divert users' attention or remind consumers about competitors' products. Reiley et al. (2010) show that when the number of search ads on top of the page increases, existing ads receive more clicks as attention is diverted by pushing the organic search results further down the page. Lewis and Nguyen (2013) find that online display advertising generates positive spillovers in online search to competitors and other related services. Sahni (2013b) shows that the addition of other products into the consumer's consideration can cause positive spillover to competitors and increase their sales. Hence, an advertiser's own benefit depends on their positioning in the category. Those who are stronger in their category benefit more from advertising. Weaker firms can overcome the lost sales leads due to spillovers by increasing the number of times the ad is shown to the consumer.

Internet technologies likewise facilitate new advertising pricing models. Similar to print, television, and radio ads, display advertising is typically sold by cost per thousand impressions (CPM). Less commonly, online display advertising is sold by cost per click (CPC) or cost per action (CPA). In online search advertising, CPC pricing is standard. Here, ads are sold in auctions in which the high bidder for a keyword (e.g., "mortgage") enjoys preferred placement in a list of ads.

Recently, Goldstein et al. (2011, 2012) proposed replacing CPM pricing for display advertising with time-based metrics, noting that a display ad impression which lasts 1 s or 10 min is sold at a fixed price. Their experiments show that the effectiveness of ads is non-linear in the time displayed; the first seconds make a strong impression on memory while later seconds contribute little. Further, displaying two short-duration ads in sequence is better for advertisers and publishers than showing one long ad. Together, these results suggest that advertisers could more reliably align the effectiveness of their ads with costs by purchasing ads based on display time instead of impressions delivered.

Publishers seeking to generate advertising revenues must consider the costs imposed upon users by advertisers over whose content they have limited control. For example, annoying ads may lead users to quit a site quickly. Goldstein et al. (2013) examine how much more one would have to pay a user to stay on a site with annoying ads as long as they would if the site lacked those ads. They paid workers for an online task while varying the compensation and the type of ad. Workers who were paid less and those who saw annoying ads worked less and thus generated fewer page views and ad impressions. A simple calculation put the compensating differential of annoying ads at \$1 per thousand impressions which exceeds the price many publishers charge for displaying annoying ads. This result suggests that showing annoying ads may cost publishers more than it earns them.

2.5 Combining revenue streams

Many online businesses combine multiple revenue streams. We focus on the bundling of information and services through crowdfunding and other means.

Increasingly, businesses rely on generating revenues from bundling products and information. Examples include online rating (e.g., Angie's List), crowdfunding (e.g., Kickstarter, Indiegogo), vacation rental (e.g., Airbnb), and online B2B (e.g., Alibaba.com) websites. These firms all aggregate market participants and generate network externalities on intermediary platforms (Yao and Mela 2008). Since the platforms generally enable transactions, platform revenues come from taking a percentage of each transaction that occurs through the platform.

Information intermediaries provide two types of value-added services. First, they aggregate information and provide access for market participants to that data, thereby facilitating matching by reducing search and transaction costs. Second, they provide rating and feedback mechanisms to maintain the credibility of the marketplace, reward high-quality users, eliminate low-quality users, and build trust among participants.

By pooling the information and product offerings of many participants, the intermediary websites reduce the transaction costs of search and matching (e.g., Ghose et al. 2012; Chen and Yao 2012). Hence, the platform facilitates transactions and charges a share of the transaction for the service. In addition, by observing the activities of others such as the accrued number of investors, participants may be able to more accurately infer the quality levels of product offerings (e.g., Zhang and Liu 2012). On one hand, this can lead to irrational herding caused by information cascades based on early mismatches (Agrawal et al. 2013). In contrast, Burtch et al. (2013) find crowding out in crowdfunding platforms, suggesting a lack of herding behavior.

3 Looking forward: open questions and challenges

Research to date has examined important questions with respect to how firms make money online and the trade-offs and difficulties involved when implementing a revenue model based on monetizing content, information, or advertising. The previous sections each end with open questions as they relate to these specific areas. Yet, while the firm's need to trade-off selling content, information, or advertising remains unchanged, evolving technology and changing consumer behavior open up new possibilities to engage with consumers through pricing or advertising or to collect consumer data. This may have implications for firms' revenue models.

A key development is that consumers increasingly turn to the mobile Internet. Initial research suggests that consumers' response to information presented on mobile screens may be different than in a PC setting. Ghose et al. (2013a) show that presenting order information is more important on the mobile Internet because of the small screen view. As of yet, there are conflicting insights on consumer response to mobile ads and their effectiveness. While some industry analysts argue that consumers prefer the free (ad-supported) version of the app over paying,[5] Gupta (2013) suggests that consumers may not welcome advertising within apps and there are only limited insights on how mobile ads interact with other forms of advertising (Nichols 2013). The increased availability of detailed consumer-level data (e.g., geolocation) in the mobile Internet points to even greater possibilities of targeting and adjusting message content to a situation (Rayport 2013). At the same time, this may increase privacy concerns. More research to evaluate these trade-offs and optimal advertising policies is needed.

Apps are perhaps the most promising way of monetizing content in the mobile Internet. The key questions here relate to whether the different usage patterns on mobile devices affect consumer willingness-to-pay for content. Put differently, does

[5] The History of App Pricing, And Why Most Apps Are Free, http://blog.flurry.com/?Tag=App+Revenue

consumers' utility from usage on a tablet or smart phone change relative to usage of the same service on a PC? If so, how can firms adjust their prices? Should firms' price discriminate between users on different devices? If a firm's ability to monetize content, information, and advertising is different for the mobile relative to the PC Internet, this may affect firms' trade-offs between revenue streams. In initial research exploring mobile revenue models, Ghose and Han (2014) estimate demand for mobile apps and examine the revenue trade-offs between various monetization options such as in-app advertising and discounts on app prices. We encourage more research that helps to understand and quantify firms' trade-offs involved in choosing their mobile revenue models.

While mobile technology is very present in our lives, it is by no means the only technological change that, we believe, should inspire future research. Below, we list several open questions that are inspired by technological change. Such a list is necessarily incomplete. Still, we think such a list provides a useful starting point for researchers interested in pursuing these topics:

1. The mobile channel does not exist independent of other channels. Should (subscription) prices be fixed across mobile, PC, and offline channels? Should firms differentiate content across platforms? How can advertising models leverage access to consumers in multiple channels? How should firms aggregate and sell the information contained in mobile, PC, and offline interactions? Can firms monetize such insights while respecting the right to privacy?
2. As digital and tracking technologies get embedded in more objects through the "Internet of things," how will that affect the relative benefits of the different revenue models?
3. How important is net neutrality to these revenue models? If Internet service providers are able to charge different firms different prices for access to end users, how will that change the nature of digital business?
4. What is the role of standards in facilitating the revenue models mentioned above? For example, if firms move to proprietary technologies for consumer tracking, or to proprietary technologies for advertising, how might revenue models and market structure change?

4 Conclusion

In this review, we have discussed how digital businesses raise revenue. We have emphasized the strengths and weaknesses of the various revenue generators and the challenges that businesses face in earning revenue online. The literature has emphasized that selling subscriptions, advertising, and customer information can all sustain digital businesses, but this research is still in its infancy.

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