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Markets for Information: An Introduction

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Abstract

We survey a recent and growing literature on markets for information. We offer a comprehensive view of information markets through an integrated model of consumers, information intermediaries, and firms. The model embeds a large set of applications ranging from sponsored-search advertising to credit scores to information sharing among competitors. We then zoom in to one of the critical elements in the markets for information: the design of the information. We distinguish between ex ante sales of information (the buyer acquires an information structure) and ex post sales (the buyer pays for specific realizations). We relate this distinction to the different products that brokers, advertisers, and publishers use to trade consumer information online. We discuss the endogenous limits to the trade of information that derive from the potential adverse use of information to the consumers. Finally, we discuss recommender systems and other information filtering systems that use artificial intelligence to predict ratings or preferences in markets for indirect information.

1. INTRODUCTION

Markets for information are ever more relevant to economic activity and welfare, in part thanks to the availability of a growing number of data sources. Trading information is not, however, merely about selling access to a database. The ability to collect, mine, and analyze large data sets creates opportunities to exchange information in the form of predictions, ratings, and recommendations and through the customizing of other products and services. At the same time, the mechanisms for trading information pose new challenges related to privacy, market power of information intermediaries, and the potential for distortions in the information sector as well as other sectors.

Several economically relevant questions have begun to emerge concerning the design of profitable information structures; the sourcing, packaging, and reselling of information; and the role of intermediation in the trade of information more generally. To date, many of these issues have been analyzed separately and in distinct settings, but no unified model exists in the literature.

In this review, we suggest a comprehensive perspective on information markets, of which, at present, we—at best—understand only individual aspects. We wish to paint a broader picture—the beginning of a complete model including all of the key factors—before focusing on specific dimensions (some related to our own work). In other words, we do not offer a settled view of what has been accomplished in the recent economics literature. Instead, we offer a proposal for how these distinct elements might fit together.

1.1. Information Products

We begin with an overview of the main mechanisms by which information is sold in practice, before discussing the role of information intermediaries and data sources. In the following sections, we focus on large brokers as the leading example of direct sellers of information, and on Amazon, Facebook, and Google as examples of indirect sellers of information. The former are firms such as Acxiom, Nielsen, and Oracle that sell information about a consumer (or a group of consumers) to downstream data buyers, such as advertisers or retailers. Building on a classification first introduced in a Federal Trade Commission report (Fed. Trade Comm. 2014), we distinguish information products along two key dimensions, as illustrated in **Table 1**:

- Who identifies the prospective consumer? Is the data broker providing the data buyer with a new list of prospects, or is the data broker appending information about an individual (or a group) that the buyer has already identified?
- Does the data broker provide information (direct sale) or access to a consumer (indirect sale)? In other words, does the data buyer have the means to independently contact the consumer, or does the data broker provide an exclusive opportunity for the data buyer to reach a consumer?

1.2. Direct Sale of Information

In the terminology of the Federal Trade Commission report (Fed. Trade Comm. 2014), original lists are the main object for sale by marketing and lead-generation companies, as well as by

Table 1 Classification of online information products

		What does the data broker sell?	
		Only information	**Access to consumer**
Who identifies the prospect?	**Data broker**	Original lists	Sponsored search
	Data buyer	Data appends	Retargeting

providers of financial data (e.g., Bloomberg). An original list is often simply a customer segment, i.e., a collection of potential consumers with certain characteristics. The audience segments sold by Nielsen, Acxiom, and Epsilon are the most common example of such lists. Individual sites can also sell original lists. For example, Evite may sell lists of consumers attending a party in a given location, and AddThis may sell lists of consumers who have shared a given news article.

Data appends reveal supplemental information about a firm's existing or potential customers. In the context of marketing, Nielsen Catalina Solutions and Oracle Datalogix connect an individual's offline and online purchases with the digital media that they consume; the Oracle ID Graph tracks firms' customers across several devices, augmenting the data collected on the firms' websites with behavioral observations from different sources; and Email Intelligence by TowerData appends demographic, income, intent, and purchase information to a merchant's own list of email addresses. Credit reporting agencies also offer reverse-lookup services and other person-specific queries for risk-mitigation purposes. For example, Equifax's Undisclosed Debt Monitoring tracks an individual borrower to identify new negative information (late payments, credit inquiries, or bankruptcy filings) that arrives between the original loan approval and the closing date. Most owners of a large database offer both kinds of products.[1]

1.3. Indirect Sale of Information

In many digital marketplaces, information is sold not only directly, but also indirectly in the form of customized goods and services. The market for sponsored-search advertising is probably the best-known example of this kind of bundled transaction. When a consumer conducts a Google search, for example, advertisers bid for a slot on a keyword search results page. Their objective is, of course, to show their link to interested consumers. Thus, by granting access to a targeted consumer population, search engines are de facto bundling advertising slots with an original list of qualified users (eyeballs). In other words, search engines forego the opportunity of directly selling information about individual users' search queries, choosing instead to leverage this information to improve the quality of their advertising product.[2]

The distinction between original lists and data appends remains valid within indirect mechanisms for the sale of information. In particular, nearly every publisher of online advertising offers the possibility of running a retargeting campaign, whereby an advertiser supplies a list of their own customers, some of whom receive an ad (or a personalized offer) on the basis of the broker's supplemental information.

Finally, the indirect sale of information is not limited to advertising markets, either. Consider a monopolist seller of financial data, as discussed by Admati & Pfleiderer (1990). As the sole owner of the information, the seller can either provide potential investors with informative signals about a stock or construct a portfolio on the basis of their information. In both cases, the seller follows Blackwell's (1951, 1953) key insight that data are only valuable insofar as they enable better decision making. The former case is a direct sale, as the data buyers can buy the stock themselves. The latter is an indirect sale because the data are never transferred, and the data buyers must instead invest in the seller's portfolio. In other words, the seller can enable the buyer to take a better action without giving away the data.

[1]The student test company ACT sells segment analysis (lists of student surveys), as well as student search services (lookups of individual records).

[2]An advertising campaign on Facebook or a display advertising campaign managed by a supply-side platform like Google's Doubleclick Ad Exchange also bundles information and advertising space. In the latter case, Google is acting as an agent for the original publisher of the advertising space.

1.4. Sourcing and Intermediation

The dark side of information markets, which we omit from the discussion above, is that the data must be sourced somewhere. In practice, the data brokers' information comes from individual sites selling their traffic flow; from mining publicly available online and offline data; and, in the case of social networks, from users' own activity. Consider the Equifax product Work Number, which sources information from centralized payroll services and sells employment and income verification (for example, to other employers or creditors). In practice, a buyer submits a list of customer accounts (or job candidates), and Equifax appends some variables of interest (e.g., whether the individual was recently demoted or fired) from its database.

Even if the value of information for a lender is transparent, what could be the incentives for businesses to link their databases to Equifax in the first place? What compensation do they require? Another interesting example is the case of the genetic testing company 23andMe, which partners with the pharmaceutical company GlaxoSmithKline, sharing some of its data to develop medical treatments (see Ducharme 2018). In this case, sequencing a patient's DNA has value for two sides of a downstream market (manufacturers and consumers of pharmaceutical products). The acquisition of information is easy for 23andMe, which can even charge for the service that it provides to consumers, but sharing the data may complicate the picture.

More generally, the nature of the information collected and its potential or actual uses determine a consumer's willingness to share it. As awareness of data-sharing practices increases, users will need to be compensated (through monetary payments or other terms of service) to make it worthwhile for them to reveal their information. This motivates our choice of a comprehensive model in which information is both bought and sold.

There are, of course, interesting aspects of markets for information that we do not cover. For example, we abstract from the verifiability problem in the sale of ideas pointed out by Arrow (1962). In some online markets, information is more easily verifiable thanks to long-run interactions. For instance, an advertising campaign contracted on a cost-per-conversion basis might enable statistical analysis of data quality over time.[3]

There is a related but distinct literature on information design and Bayesian persuasion, as surveyed in recent contributions by Bergemann & Morris (2019) and Kamenica (2019). This large literature considers a relatively narrow question of how a sender or designer can achieve an objective only by committing to a policy of information revelation. This literature does not study the price of information, nor does it consider markets for information. For this reason, there is currently not much overlap between these areas of research. Yet, as we indicate in Section 4, in principle there are many applications that take an information design problem as an input and map it into a market for information question.

1.5. Outline

Section 2 illustrates our main model. We highlight the role of market power for the data brokers. We show how intermediaries can derive positive profits through the sale of information even if this sale reduces total surplus. We also emphasize the limits of relying on a heavily parameterized model, such as the Gaussian model, where information structures can be captured by only a few moments.

Section 3 zooms in to one of the central elements of information markets: the design of the information. We adopt the perspective that information is an input into a (strategic) decision problem and study the optimal sale of supplemental information to heterogeneous, privately informed

[3] Hörner & Skrzypacz (2016) provide a solution based on gradualism in the provision of information.

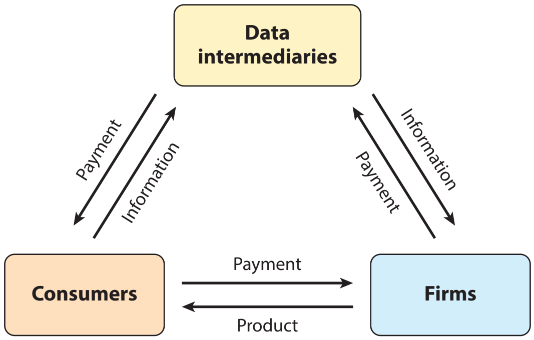

Figure 1

Market for consumer data.

agents. In doing so, we distinguish between ex ante and ex post sale of information and relate the difference between these types of sale to the two kinds of products (original lists and data appends) described above.

Section 4 analyzes equilibrium phenomena that can be understood through the lens of our model. We discuss the ratchet effect associated with using information for price discrimination purposes and the role of ratings, predictions, and recommender systems as markets for indirect information.

Section 5 describes future research directions and open questions.

2. BUYING AND SELLING INFORMATION

We first present a basic model of a market for information in Section 2.1. The model has three sets of constituent players: (*a*) consumers, who have private and possibly imperfect information about their preferences; (*b*) firms, which can offer products to the consumers while choosing prices and quantities; and (*c*) data intermediaries, who collect, aggregate, and distribute information between the consumers and the firms.

Our leading example is the market for consumer data. The data are being collected, either directly or indirectly, by data intermediaries. These data intermediaries offer the data to firms, which use the data to tailor their product offerings to the consumers. The consumers reveal the information either directly to the data intermediaries or indirectly through their past behavior and purchases. A diagrammatic representation is given in **Figure 1**.

In Section 2.2, we discuss important contributions to the literature that focuses on specific aspects of the interaction described above.

In Section 2.3, the analysis of the information market is restricted to bilateral trade. Thus, for example, Admati & Pfleiderer (1986) assume that the data intermediary possesses all of the relevant information at the outset, and their analysis thus focuses on the pricing policy of the data intermediary vis-a-vis the firm.

In Section 2.4, we relate the model to the large literature on information sharing among oligopolists. In this case, the competing firms individually have all relevant information already and do not need to elicit the information from the consumer. In addition, the data intermediary is restricted to transmitting either all information or none and acts only to coordinate the industry but does not pursue an objective separate from the industry (see Raith 1996, Vives 1984).

2.1. An Integrated Model

To gain a comprehensive understanding of information markets, we begin by presenting a model that contains all three elements outlined above. We then present some first results based on our recent work (Bergemann & Bonatti 2018) and relate this work to a larger literature on the value of information in strategic settings.

2.1.1. Consumers. We consider a model with finitely many consumers, $i = 1, \ldots, N$. The willingness to pay of each consumer is given by w_i:

$$w_i \triangleq \theta + \theta_i. \tag{1}$$

The willingness to pay w_i of consumer i is the sum of a common and an idiosyncratic component, θ and θ_i, respectively. Each consumer maximizes a quadratic utility function:

$$u\left(w_i, q_i, p\right) \triangleq w_i q_i - p q_i - \frac{1}{2} q_i^2. \tag{2}$$

Thus, w_i is the willingness to pay for the first unit of the product. We sometimes refer to w_i as the value or valuation of consumer i. Consumer i maximizes their utility by choosing the appropriate consumption decision, q_i, at a unit price p. The consumption variable q_i may be interpreted as a quantity or quality variable.

At the outset, each consumer does not observe their true willingness to pay, but rather receives a noisy signal s_i. The signal s_i represents the data-producing aspect of the consumer. When the consumer makes the purchase decision, we assume that consumer i will have learned w_i. For example, we may interpret s_i as the search term that consumer i enters into a search engine like Google or their activity on a social network like Facebook.

The privately observed signal s_i can include a common and an idiosyncratic shock, which we denote by ε and ε_i, respectively:

$$s_i = \theta + \varepsilon + \theta_i + \varepsilon_i. \tag{3}$$

For the moment, all the variables are jointly normally distributed:

$$\begin{pmatrix} \theta \\ \theta_i \\ \varepsilon \\ \varepsilon_i \end{pmatrix} \sim N\left[\begin{pmatrix} \mu_\theta \\ \mu_{\theta_i} \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\theta^2 & 0 & 0 & 0 \\ 0 & \sigma_{\theta_i}^2 & 0 & 0 \\ 0 & 0 & \sigma_\varepsilon^2 & 0 \\ 0 & 0 & 0 & \sigma_{\varepsilon_i}^2 \end{pmatrix}\right]. \tag{4}$$

The joint prior distribution is commonly known by all market participants.

2.1.2. Firms. There are finitely many firms that can supply the products to the consumers. Each firm $j = 1, \ldots, J$ has a linear production cost $c_j(q) = c_j q$ for some nonnegative constant c_j. Each firm seeks to maximize its expected profit:

$$\pi_j\left(q_j, p\right) = \mathbb{E}\left[\left(p - c_j\right) q_j\right]. \tag{5}$$

2.1.3. Data intermediary. The data intermediary collects the information from the individual consumers and then sells it to the firms. The firms use the information to improve their price and quantity policy. Thus, the data intermediary does not initially possess any information on their own, but rather collects the data from the consumers and then redistributes it among the firms.

The data intermediary makes a bilateral offer to each consumer i, under which the consumer shares their information with the data intermediary. The data intermediary offers a transfer fee $f_i(\mathcal{I}_i)$ to consumer i as a function of the transmitted information $\mathcal{I}_i$:

$$f_i : \mathcal{I}_i \to \mathbb{R}. \qquad 6.$$

The information structure $\mathcal{I}_i$ being transmitted can simply be the entire information of consumer i or some, possibly noisy, statistic of their information.

Similarly, the data intermediary offers to share information about the consumers with the firm j and in exchange asks for a transfer fee $g_j(\mathcal{I}_j)$ as a function of the transmitted information:

$$g_j : \mathcal{I}_j \to \mathbb{R}. \qquad 7.$$

The data intermediary can convey all of the information at their disposal or offer a certain statistic of their information. We describe this in some detail below. The transfer fees are lump-sum payments subject only to the participation constraints (i.e., the outside options) of the consumers and the firms. The equilibrium is obtained by backwards induction. First, each firm determines an optimal selling policy for its product given its information. This results in a quadratic value for the firm and the consumers. When we solve the problem recursively, the data intermediary makes a take-it-or-leave-it offer to the firm and the individual consumer for the entire information structure, based on the expectation of their interaction.

2.2. Intermediation and Information

In this section, we present some basic results and insights from a specific version of the above framework. We consider a single data intermediary and a single firm that offers its product to the consumers. The firm uses the information obtained by the data intermediary to tailor the price to the level of market demand. For now, we assume that the firm offers a uniform price to the market of consumers.

With a single firm, the pricing problem essentially becomes a problem of third-degree price discrimination, where different realizations of the information play the role of market segments. The firm, given the estimate about the market demand, forms a linear pricing rule that attempts to extract much of the consumer surplus. With the quadratic utility function of the consumers and the constant marginal cost function of the firm, this framework is the classic linear demand problem analyzed by Robinson (1933) and Schmalensee (1981). Robinson (1933) finds that the average quantity supplied is the same with or without price discrimination. Schmalensee (1981) finds that, to the extent that prices are more correlated with the willingness to pay under third-degree price discrimination, the firm receives a larger profit, while the consumer welfare and total welfare are lowered.

The classic analysis of Schmalensee (1981) would suggest that, in view of lower social welfare due to third-degree price discrimination, there might not be room for a data intermediary to make profits. Thus, the question is how there can be information sharing and information mediation in equilibrium.

As the information is ultimately used for price discrimination, the individual consumer asks for compensation for the transfer of information. However, to the extent that the private information of agent i is information about their idiosyncratic demand as well as the aggregate demand, the individual consumer can only request a compensation at the margin. By contrast, the data intermediary can charge the seller for the entire value of demand information. Thus, there is a friction between marginal pricing vis-a-vis the consumer and average pricing vis-a-vis the producer. This creates the opportunity for inefficient use and transfer of information by an intermediary with market power.

This divergence between the marginal cost of eliciting the information and the average benefit from transmitting the information has some immediate implications for the position of the data intermediary. Consider a given informational environment as described by the vector of variances,

$$\Sigma = \left(\sigma_\theta^2, \sigma_{\theta_i}^2, \sigma_\varepsilon^2, \sigma_{\varepsilon_i}^2\right), \tag{8}$$

and suppose that the intermediary simply aggregates the signals of the individual consumers and transmits the information to the firm in terms of a posterior estimate of the aggregate demand. Bergemann & Bonatti (2018) find that there is always a threshold $\overline{n}$ such that the information intermediary can enter the market and receive positive profits if and only if the number N of consumers satisfies $N > \overline{n}$. The location of the threshold is determined by the size of the demand uncertainty $\left(\sigma_\theta^2, \sigma_{\theta_i}^2\right)$ and the informativeness of the signals of the consumers $(\sigma_\varepsilon^2, \sigma_{\varepsilon_i}^2)$.

The individual consumer conveys information to the intermediary both about their idiosyncratic demand shock and about the aggregate demand shock. In equilibrium, the intermediary will learn a lot about the aggregate shock from the other consumers. However, to the extent that the information conveyed by the individual consumer i is about their idiosyncratic shock, the consumer anticipates the response of the firm and will require compensation from the data intermediary. With a sufficiently large number of consumers, the information intermediary can filter a substantial amount of the idiosyncratic noise. At the same time, as the number of consumers increases, the firm already has a more precise estimate of the average idiosyncratic shock. Consequently, the firm will optimally respond less to each idiosyncratic shock, and thus each individual buyer anticipates an attenuated response to their idiosyncratic demand shock and requests a lower contribution.

This suggests that the scope for profitable intermediation is determined by the relative size of the idiosyncratic and the aggregate shocks. The differential responsiveness to the idiosyncratic and the aggregate shocks directly suggests comparative static results with respect to the relative size of the two different sources in the demand shock. Indeed, suppose we fix the informational environment, except for the variance of the aggregate demand shock, thus: $\Sigma_{-\theta} = \left(\sigma_{\theta_i}^2, \sigma_\varepsilon^2, \sigma_{\varepsilon_i}^2\right)$ and $N > 1$. In this case, there exists a threshold $\overline{\sigma}_\theta$ such that, for all $\sigma_\theta > \overline{\sigma}_\theta$, the profit of the data intermediary is positive, and for all $\sigma_\theta < \overline{\sigma}$, the profit of the intermediary is negative. Thus, as the size of the aggregate shock becomes sufficiently large, there develops scope for information intermediation.

Similarly, as the idiosyncratic shock becomes sufficiently small, information intermediation can again arise profitably. Thus, we can fix the informational environment, except for the variance of the idiosyncratic demand shock, thus: $\Sigma_{-\theta_i} = \left(\sigma_\theta^2, \sigma_\varepsilon^2, \sigma_{\varepsilon_i}^2\right)$ and $N > 1$. In this case, there exists a threshold $\overline{\sigma}_{\theta_i}$ such that, for all $\sigma_{\theta_i} < \overline{\sigma}_{\theta_i}$, the profit of the intermediary is positive, and for all $\sigma_{\theta_i} > \overline{\sigma}_{\theta_i}$, the profit of the intermediary is negative.

Above, we assume that the information intermediary simply collects the raw information provided by the consumers and then transmits a posterior estimate of the aggregate demand to the firm. Thus, the intermediary transfers the information from the consumer to the firm in its entirety. There are circumstances under which the intermediary may wish to add noise to the information conveyed to the seller.

The optimal information policy for a data intermediary remains an open question. Bergemann & Bonatti (2018) provide some initial insight regarding the nature of information design in this multivariate normal setting. Suppose we restrict attention to the addition of idiosyncratic and aggregate noise in the estimate provided to the firm. We then establish that the intermediary will never want to add idiosyncratic noise to the data of the individual consumer. By contrast, the addition of aggregate noise into the transmitted data can increase the revenue of the data intermediary in some informational environments. For instance, there exists an intermediate range of the number of consumers such that the data intermediary cannot attain a positive profit with complete information transmission but can attain a strictly positive profit with noisy information transmission.

Indeed, while the noise will lower the value of the information to the firm and thus the revenue that the intermediary can receive from the firm, it also lowers the compensation that the individual consumer will require. As the noise will make the aggregate response less sensitive to the information provided by the consumer, it will in particular dampen the response to the idiosyncratic information provided by the consumer. On balance, the data intermediary then wishes to lower the informativeness to decrease the necessary compensation to the consumers. As N grows large, the need to add noise will eventually disappear, as common shocks will outweigh idiosyncratic shocks in the estimation of the average demand.

2.3. Selling Information to Competing Firms

The seminal contribution by Admati & Pfleiderer (1986) analyzed a model where traders buy information from a monopolistic seller. From the outset, the data seller is assumed to be in possession of the information and thus in complete control of the entire database. Initially, the traders all share a common prior regarding the value of the asset. Each trader can acquire additional information regarding the value of the asset from the monopolistic seller. There is a continuum of traders, and each trader submits their demand as a function of their private information. The equilibrium price of the asset is determined in a speculative market formalized as noisy rational expectations equilibrium. The true value of the asset is common to all the traders. The information seller therefore faces the possible dilution of the value of information due to its leakage through informative prices.

The first set of results of Admati & Pfleiderer (1986) concerns the optimal selling policy of the information monopolist. The seller may or may not grant access to the information to all buyers. In addition, the seller may or may not add noise to the initial information. Admati & Pfleiderer (1986) present conditions under which each one of the possible four combinations can emerge as an optimal informational policy. They then consider the personalized sale of information. In this case, the seller is allowed to add idiosyncratic noise to the common value signal for each trader. Admati & Pfleiderer show that the seller of information may prefer to sell noisier versions of the information. Moreover, to obtain higher profits, it is desirable for the seller to sell different signals to different traders, so that the added noise realizations do not affect equilibrium prices. One way of doing so, which does not require discrimination, is to sell identically distributed personalized signals to each of a large number of traders.

In an oligopoly setting with incomplete information, Bergemann & Morris (2013) analyze the information structure that guarantees the highest industry profit. Like Admati & Pfleiderer (1986), they find that, if the strategic substitutes are sufficiently strong, then a noisy signal in which each firm learns the common value subject to idiosyncratic noise sustains the largest possible level of industry profits. In the analysis of Admati & Pfleiderer (1986), the monopolistic seller, in turn, extracts the value of the industry profits by charging the individual traders for their private information.[4]

[4]The reader is also referred to Bimpikis et al. (2019) for a discussion of the nature of downstream competition and its implications for selling information in oligopolies.

Admati & Pfleiderer (1990) extend their analysis to allow for two distinct methods of selling information. As do Admati & Pfleiderer (1986), they allow for the direct sale of information to the investors, but they also allow the seller of the information to bundle the information with a product, in particular, a portfolio whose composition depends on the available information. The analysis mostly considers a linear pricing policy for the portfolio and compares the revenue from a direct and an indirect sale of information. They find that indirect sale is more profitable when the externality in the valuation of information is relatively intense.[5]

Admati & Pfleiderer (1990) also consider the possibility that the seller can use a two-part tariff. In this case, the indirect sale always dominates the direct sale. In an interesting discussion, they also consider the possibility that the traders have different private information. In this case, the direct sale of information can improve the revenue as the seller can unbundle the initial information of the trader and the supplemental information.

In an extension to their earlier arguments, Admati & Pfleiderer (1988) allow the seller of information to trade strategically on their own accounts, as well. The information seller can now either trade their information, sell their information, or both. In any of these cases, the seller commits to a policy in advance. Admati & Pfleiderer show that the optimal policy depends on the degree of risk aversion of the information buyer and the information seller. In particular, if the buyer's risk aversion increases, then the value of trading on the information decreases, and the value of selling information directly increases.

2.4. Information Sharing Among Competing Firms

There is a large literature on information sharing among oligopolists, the main results of which are succinctly presented by Raith (1996). The main question dealt with by this literature, which began with the work of Novshek & Sonnenschein (1982), Clarke (1983), Vives (1988), and Pagano & Jappelli (1993), is whether competing firms, all with partial information, may have an incentive to share information through an intermediary, such as a trade association. Relative to this literature, the model of information markets we present above has two important features. First, in the earlier models, the information was collected and shared by an intermediary, such as a trade association, that merely organized and facilitated the exchange between the oligopolists but that had no genuine interest or market power. Second, the firms had all the information to begin with and did not have to collect the information from the consumer.

Our model introduces consumers and describes the limits of information sharing in markets. There remain many interesting questions to be pursued. Even if the individual firms already have all the relevant demand information, one might ask under which conditions an intermediary could profitably collect and redistribute the information among the competing firms. In this respect, the credit rating and monitoring agencies play the role of information intermediaries. The credit rating agencies both collect information about the borrowers and lenders from a given bank and provide this bank with additional information about the credit worthiness of a new or established client. Thus, these agencies both collect and redistribute demand information among the financial institutions.

The earlier literature on information sharing left a limited role for information design. In particular, while the firms were allowed to add noise to their private information, the intermediary was restricted to simply aggregating and reporting the received information in the same format to all of the firms. The restrictiveness of this analysis was documented by Bergemann & Morris

[5]As mentioned in Section 1, the distinction between direct and indirect sales is similar to the distinction between pure information intermediaries and search engines or social platforms that jointly price information and access to the consumer.

(2013). They investigated the role that private information from the competing firms can play in the realization of equilibrium values, prices and quantities, and the welfare of the market participants. Among other results, Bergemann & Morris (2013) identify the information structure that maximizes the industry profits as a function of the demand and supply conditions in the market. Similar to the earlier results of Admati & Pfleiderer (1986), they show that the optimal information structure has each individual firm receive private information with idiosyncratic noise that limits the correlation in the quantity choices by the firms.

2.5. Applications and Variations of Information Markets

The game form described in Section 2.1 allows for many variations, each of which would allow for a more precise match between the model and the specific information market under consideration. Taken literally, the tripartite model describes a data intermediary who collects information from consumers through a survey, compensates the consumers for their participation in the survey, and then repackages the information to the firms. This is close to the business model behind Nielsen Family and Nielsen Panel, which collect TV viewing and scanner purchase data, respectively, from individual consumers. Several Internet startups, such as Datacoup and Datawallet, are preparing more comprehensive data offerings using the blockchain technology. Agarwal et al. (2018) offer an algorithmic solution for a data marketplace that matches buyers and sellers for training for machine learning tasks.

The sponsored-search auctions on search engines that determine the listings on the search engines run by Google, Microsoft, and Amazon offer a second set of examples. In these auctions, the consumer enters a search term on the search engine. The search term is then sold, possibly together with additional data, through a generalized second price auction. Each of the competing advertisers seeks to attract the searching consumer to its own website, where the consumer can find the possibly matching products and services. Edelman et al. (2007) and Varian (2007) offer a comprehensive analysis of this auction format. In this context, the price for the information is determined through an auction mechanism rather than a posted price or a menu of prices.

A second important aspect of the sponsored search is that the information is sold item by item, i.e., search term by search term, rather than as a bundle of search terms. Thus, in the language of information economics, the information is sold at the interim level, separately for each realization, rather than at the ex ante level for an entire distribution of possible realizations, as in the model discussed above. By contrast, in the context of display advertising, the other large segment of online advertising, the displays are frequently sold in the form of a campaign with a prespecified budget and contractual requirements (see Mirrokni & Nazerzadeh 2017). In turn, the contract between the advertising platform and the advertiser then resembles the ex ante contracting analyzed above.

The search engines frequently combine the search term with supplemental information about the characteristics of the searching consumer. They can thus refine the informational item that is being sold to allow more targeting. An implication of this increased differentiation is the possibility of thinner markets and less competition. Bergemann & Bonatti (2011) develop a model with many advertisers and many media to investigate the implications of targeting for the price of advertising. Levin & Milgrom (2010) discuss this issue in terms of splits and conflation of product categories. Eliaz & Spiegler (2016) argue that a statistical criterion of correlation should guide the optimal broad match between search terms and consumer characteristics.

We distinguish above between direct and indirect sales of information. The sale of display advertising by one of the competing advertising networks can be viewed as an example of indirect sale of information. The sale of information to an advertiser, namely information about a specific consumer with specific characteristics on a specific website, is bundled with the placement of display advertising.

The transfer of information from the source, the consumer, to the intermediary often does not happen in one stop, but instead is itself intermediated. For example, in the world of consumer financial data, it is often the banks and financial institutions that collect the individual data, such as the credit history of a personal account. These firms then forward the data to a credit bureau and then buy additional data about their own consumers and possible new prospects.

A noteworthy aspect of the exchange of information is that, in many instances, the consumer transmits the information to an intermediary either at a zero price or in conjunction with access to some other benefits. Thus, the purchase of information can be direct or indirect, as is the case for the sale of information. For example, Facebook does not compensate the user for the information generated about its network, but in exchange for their information, the user receives free access to an electronic platform to connect with friends. Similarly, the search engine provides organic search results in addition to the sponsored search listings.

The apparent lack of direct monetary compensation for information may to a large extent be due to the well-known problem of adverse selection that arises with compensated surveys. The compensation may induce nontruthful reporting behavior and/or select an unfavorable segment of the population. The desire to make truthful reporting incentive compatible then provides a strong reason to bundle the elicitation of information with an allocation that supports truth telling. For example, in a social network, the information provided by the individual is accessible by the members of the network and is thus verified. In the above example of the testing services provided by ACT for high school students, the survey occurs in the context of college application, where the initial information provided may later be cross-checked by the colleges. More immediately, any purchase or browser data present revealed preference data about the consumer.

3. MECHANISM DESIGN APPROACH TO SELLING INFORMATION

We now zoom in to one of the critical elements in the analysis of information markets: the design of the information. In the basic model of the market for information, as presented in Section 2, we restrict attention to multivariate normally distributed variables. The assumption of normality renders the general analysis tractable. In particular, it reduces the design of the information to a choice of the variance and covariance matrix.

We examine with more detail and more depth the choices in the design of information. To do so, we focus on the interaction between a single seller and a single buyer of the information. This allows us to examine more general payoffs and more general information structures. In particular, we allow for non-Gaussian information structures and will be explicitly concerned with higher moments, beyond the second moment, of the information structure.

In this section, we take a mechanism design approach to selling information when data buyers are privately informed about their beliefs or preferences. We initially focus on direct sale of information where contracting takes place at the ex ante stage: In this case, the buyer purchases an information structure (i.e., a Blackwell experiment), as opposed to paying for specific realizations of the seller's informative signals. With reference to our introductory classification, this corresponds to purchasing a data append. We then turn to different contracting assumptions that extend the analysis to selling individual signal realizations (i.e., original lists) and to the indirect sale of information.

3.1. Ex Ante Pricing: Selling Experiments

Bergemann et al. (2018) consider a model with a single data buyer who can invest in a consumer at fixed conditions. For example, a lender must decide whether to grant a loan to a prospective

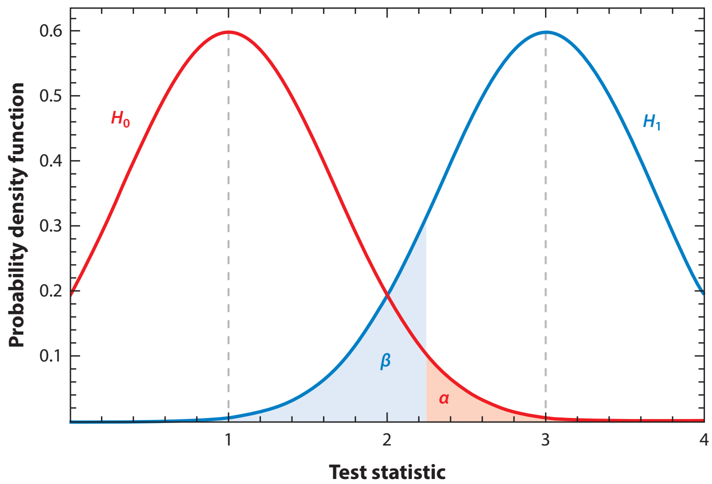

Figure 2

Conditional density of null hypothesis H_0 and alternative hypothesis H_1. A given threshold for the realization of the test statistic induces a type I (α) and type II (β) statistical error.

borrower at the prevailing market rate. The data buyer is a Bayesian decision maker with private type θ, representing their prior beliefs about the credit worthiness of the borrower. These beliefs are the buyer's private first-party information. Therefore, different buyer types θ have different valuations for additional information. A monopolist data seller designs and sells Blackwell experiments on the basis of their third-party information. The data buyer purchases a single experiment, updates their beliefs by appending the seller's data to their existing information, and ultimately chooses an action. Bergemann et al. (2018) focus on designing the revenue-maximizing menu for the seller. Bergemann & Morris (2019) provide a unified perspective on information design in games.

The best way to frame the problem is through Bayesian hypothesis testing. Suppose the data broker has access to a continuous riskiness measure that is informative of the borrower's underlying risk profile. The lender wants to test a null hypothesis H_0 (borrower is low risk) against an alternative H_1 (high risk). An example of such a binary statistical test is given in **Figure 2**. A statistical hypothesis test compares a null hypothesis against an alternative hypothesis. The hypothesis test is characterized by the choice of threshold, which yields type I and type II statistical errors, as illustrated in **Figure 2**. A type I error is the rejection of a true null hypothesis, while a type II error leads to a failure to reject a false null hypothesis.

The central issue for the data seller is that they do not know the data buyer's prior beliefs and, thus, the buyer's willingness to pay for the information provided by a specific statistical test. In response to the heterogeneity in the demand information, the seller can design any binary (pass/fail) test that reports whether the riskiness measure is above or below a particular threshold. Each test is intended for a different buyer type θ and yields a different combination of type I and type II statistical errors (α, β). **Figure 3** illustrates the feasible statistical tests in terms of the statistical errors with which they are associated. The set of feasible tests is determined by the information available to the seller. In the absence of any information, the seller can only offer statistical tests in which the sum of the errors always equals 1. This is represented by the red line in **Figure 3**. The set of feasible tests becomes larger the more information the seller can provide.

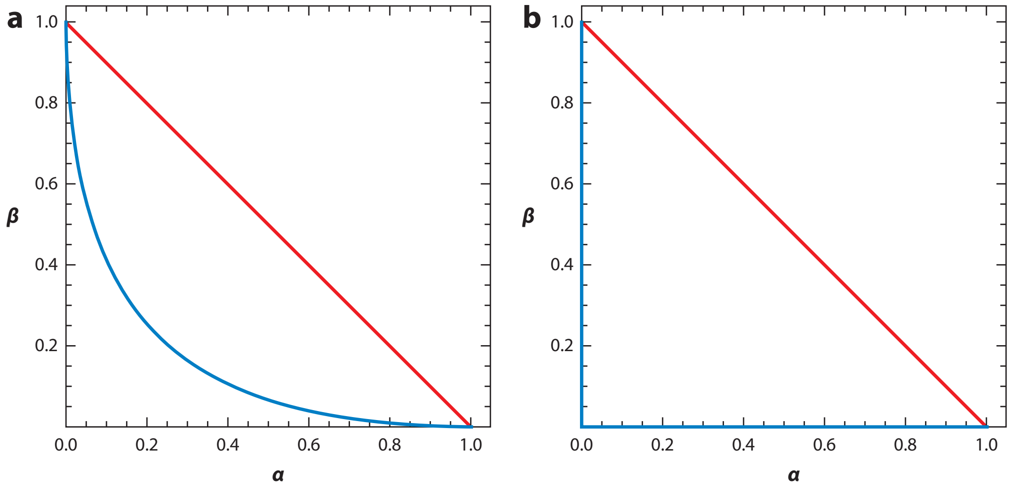

Figure 3

The feasible information structures are represented in terms of their statistical errors. The type I and type II errors are represented by α and β, respectively. The upper bound on the statistical errors is given by the red line. The lower bound (*blue line*) depends on the quality of the information available to the seller. The information is imperfect in panel *a* and perfect in panel *b*.

Figure 3*a* illustrates the set of feasible tests when the seller has only partial information, and **Figure 3*b*** illustrates the feasible set when the seller has complete information. In the latter case, the seller can offer a statistical test in which either or both statistical errors are minimized at zero.

The main idea behind the revenue-maximizing mechanism for the information seller is akin to offering damaged goods to low-value buyers. However, in the sale of information goods (Shapiro & Varian 1999), product versioning allows for richer and more profitable distortions than are possible with physical goods. This is due to a peculiar property of information products: Because buyers value different dimensions of the state space—the space of uncertainty—the willingness to pay of the buyer varies with the specific dimension about which information is provided. For example, in the context of credit markets, very aggressive lenders are interested only in very negative information and are willing to grant a loan in the absence of such information.

The seller can thus leverage the key insight of Blackwell—that information is only valuable if it changes optimal actions—to screen the buyer's private information. Bergemann et al. (2018) uncover systematic distortions in the information provided under the optimal menu, i.e., in the distribution of states and signals that are associated with monopolistic screening. In particular, their results impose restrictions on the types of statistical errors incurred by data buyers when data sellers enjoy market power. With binary states and actions and no constraints on the statistical errors (α, β), each buyer incurs only one type of statistical error. More generally, all optimal tests minimize the type II error β for any level of type I error α, i.e., they lie on the lower boundary of the feasible set in **Figure 3**. Separation in the optimal menu is then supported by the differences in the error structure of each test and by the buyers' heterogeneous preferences over statistical errors.[6]

[6]Heterogeneity in the demand for information can also arise from privately different preferences over actions (e.g., heterogeneous costs of lending). This formulation is slightly simpler than that of private beliefs because the buyer's type is not correlated with the realization of the seller's experiment. This distinction affects the optimal mechanism except in the special case of two states and two actions (Kolotilin et al. 2017).

Data Module	Description	Basic	Plus	Premium
Base Monitoring	• Debt to Income (DTI) **New!** • Trade Account Number • Date to File • Date Opened • Forward and look back periods 120 days	X	X	X
New Collection	Any new collection fcund on borrower's file **New!**		X	X
New Public Record	Any new bankruptcies, foreclosures, judgments, or liens found on borrower's file **New!**		X	X
Balance Changes	Any increase in or zero out of balance on borrower's tradeline balance on borrower's file **New!**		X	X
Scheduled Payment	Any increase in scheduled payment amount on borrower's tradeline **New!**		X	X
New Late Payments	Any new late payments 30, 60, 90, 120 days past due **New!**		X	X
Tradeline Bankruptcy	Any new accounts found to be in bankruptcy on borrower's tradeline **New!**		X	X
Tradeline Collections	Any new accounts found to be in collections on borrower's tradeline **New!**		X	X
TransUnion® Inquiries	Inquiries sourced from TransUnion Pre/Post Closing Mortgage Notifications (PCMN) **New!**			X
Experian℠ Inquiries	Inquiries sourced from Experian's Retention Triggers℠ for Mortgage (MURS) **New!**			X

Figure 4

Screenshot of the Equifax Undisclosed Debt Monitoring product sheet. Reproduced from Equifax (2015).

A concrete implication of these results is that it is never optimal for the seller to damage information products by adding unbiased noise. Instead, information is degraded by revealing only a portion of the available data to the buyer.[7] For concreteness, consider the case of Undisclosed Debt Monitoring, an information policy offered to financial institutions by the data broker Equifax. Equifax offers this risk-management product in three different versions. As shown in **Figure 4**, the three versions (Basic, Plus, and Premium) differ only in the number of red flags that the lender receives if the buyer's history includes some particularly informative negative events.

Assume for simplicity that it is optimal for the lender to grant the loan if and only if Equifax has no negative information about the borrower. In this example, no low-risk borrower would ever be turned down, but some high-risk borrowers would receive a loan.

There would be, of course, other ways of releasing degraded information: delaying its time release, coarsening the signals, or adding noise. In this case, instead, the seller chooses to provide only a subset of the available red flags. Additional restrictions come from the structure of the optimal menu, where the seller offers packages that provide an increasing amount of information, rather than allowing for linear or additive pricing of several packages. Furthermore, in the case of binary states and actions, Bergemann et al. (2018) show that only a binary choice is provided (premium information versus basic information), even with a continuum of buyer types.

3.2. Ex Post Pricing: Selling Realizations

Above, we focus on the sale of data appends in the form of (ex ante) information structures. In contrast, the sale of original lists can be modeled as an informative experiment that reveals whether a potential consumer matches a prespecified set of characteristics, in which case the buyer receives a contact and pays a price. This is true both when an original list is sold directly (e.g., in the case of information about ACT test takers) and when it is sold indirectly (as in the case of sponsored

[7]The provision of noisy information can be profitable when multiple buyers compete in a downstream market: Kastl et al. (2018) show that a monopolist seller may supply imprecise information to perfectly competitive firms to limit the distortions due to internal agency conflicts; Malenko & Malenko (2019) show that a proxy advisor may only sell partial information to strategic voters.

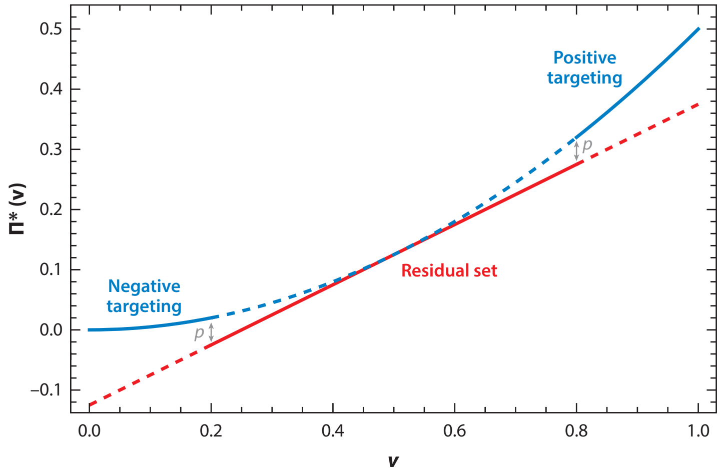

Figure 5

The value of a match between consumer and advertiser is linear in the willingness to pay, v, of the consumer absent any information (*red line*). With additional information, the seller can realize additional benefits that are convex due to the value of information (*blue curve*). p is the unit price of information and $\Pi^*(\mathbf{v})$ is the complete-information profit level.

search or targeted display advertising). In these cases, the price paid by the buyer depends on the realization of the seller's information.

Bergemann & Bonatti (2015) consider the trade of information bits (browser cookies) that are inputs into a decision problem. In particular, a single firm (a buyer of information) has heterogeneous match values with a set of consumers. To realize the potential match value, the firm must choose a continuous investment level. The optimal investment level (e.g., advertising spending) depends on the consumer's match value v. To capture the role of browser cookies, we consider a special information structure, namely one in which individual consumers' types are learned either perfectly or not at all. Through the purchase of information, the firm is then able to segment consumers into a targeted group that receives personalized levels of advertising and a residual set that receives a uniform level of advertising. Finally, the buyer pays a constant price p per targeted consumer.

We establish that advertisers purchase information on two convex sets of consumers, specifically those with the highest and those with the lowest match values (see **Figure 5**). In other words, advertisers do not buy information about every consumer type. Instead, they optimally choose a convex residual set, over which they estimate the match value. This excluded set minimizes the prediction error. Under stronger conditions on the matching technology and on the distribution of match values, the data-buying policy takes the form of a single cutoff match value. That is, advertisers buy information about all users above (positive targeting) or below (negative targeting) a cutoff.

Babaioff et al. (2012) study a related model of selling lists (i.e., pricing conditional on signal realizations) when buyers are heterogeneous and privately informed. In particular, the data buyer's value depends on two variables: One is known by the seller, while the other is the buyer's type. Their paper develops algorithms to characterize the optimal mechanism and derives conditions under which the seller can extract the entire surplus, exploiting the correlation between the seller's information and the buyer's type.

Eső & Szentes (2007a) and Li & Shi (2017) consider the case where signal realizations are not directly contractible, but the buyer's actions are. In these models, the seller of a good controls both its price and the information provided to the buyer, with the goal of screening the buyer's private, partial information. In the context of online markets, the seller is a provider of advertising space who can offer arbitrarily fine targeting criteria to advertisers. (Recall the above discussion of indirect sales of information through Facebook or Google advertising.)

Eső & Szentes (2007a) focus on the case where the seller releases information that is orthogonal to the buyer's type. (This is without loss if, for example, the buyer's type is a preference parameter, and the seller reveals information about the quality of the product.) The seller-optimal mechanism when a single buyer is present reveals all the information and offers a menu of European call options where a lower strike price costs more up front. In the case of competing buyers, a two-stage handicap auction is optimal. Intuitively, a positive strike price distorts the buyer's decisions, but the result suggests that it is more profitable to distort ex post decisions than to distort the initial information. Li & Shi (2017) show that discriminatory disclosure of information—providing different buyer types with different signals—dominates full disclosure when the seller is not restricted to orthogonal disclosure.

In many cases, an advertiser can use additional third-party data to refine the targeting criteria offered by a publisher. Eső & Szentes (2007b) consider a related model of selling advice. By reinterpreting their model, we can develop a case in which an advertiser buys information about a prospective consumer before deciding whether or not to advertise their product. As the transaction takes place contextually to the advertising campaign, the data buyer's action is contractible. In some special cases, the data seller discloses the entire information to all buyer types. Distortions to the buyer's actions then come from a marginal price of advice. In other words, the data seller grants access to their database (perhaps against a subscription fee) but charges a marginal price for the data only upon the buyer's investment. In practice, it is often the case that the advertiser is charged for data on a cost-per-mille basis, in which case the price of data adds to the marginal cost of the advertising space.

4. THE LIMITS TO TRADING INFORMATION

We begin this section by discussing price discrimination as a well-understood source of the value of information. This then brings us to the limits of how information can be traded when consumers must be given incentives to generate or reveal information without direct monetary transfers for their data. In particular, Section 4.2 describes the ratchet effect and the problem of sourcing information from the consumer's actions. Section 4.3 illustrates how the use of ratings, recommender systems, and information aggregators determines the market's ability to obtain new information from consumers.

4.1. Price Discrimination

An important use for additional information about demand is for engaging in price discrimination. We focus our discussion on third-degree price discrimination.[8] The large literature on third-degree price discrimination, beginning with the classic work of Pigou (1920), examines what happens to prices, quantities, and various measures of welfare as the market is segmented. As every segment is offered a different price, there is scope for the producer to extract more surplus from

[8]A seller engages in third-degree price discrimination if they use information about consumer characteristics to offer different prices to different market segments. If, indeed, a monopolist has complete information about the buyer's willingness to pay, then they could engage in perfect or first-degree price discrimination. The seller can also offer a menu of choices, in terms of quality or quantity, to screen among different segments of the market; this process is referred to as second-degree price discrimination.

the consumer. Yet to the extent that the producer can tailor the price to each segment, more consumers might be reached, and there might be less exclusion. With the increase in available information about consumer demand comes increasing flexibility in the ensuing market segmentation: The platform that provides the data or the product seller can to a large extent determine how to optimally segment a given aggregate demand.

Bergemann et al. (2015) analyze the limits of price discrimination. They show that the segmentation and pricing induced by the additional information can achieve every combination of consumer and producer surplus such that (*a*) consumer surplus is nonnegative, (*b*) producer surplus is at least as high as profits under the uniform monopoly price, and (*c*) total surplus does not exceed the surplus generated by the efficient trade.

The implications of an information structure for consumer surplus are analyzed by Roesler & Szentes (2017). They consider a model where the buyer's valuation for the object is uncertain, and the buyer can commit to an optimal information structure that, in turn, affects the price-setting behavior by the seller. They show that the resulting outcome leads to efficient trade under unit-elastic demand.

The size of the possible gains, for both consumer and producer surplus, relative to the uniform pricing rule suggests that there is substantial scope for the provision of additional information. The large range of feasible pairs of consumer and producer surplus implies that there may be many possible business models for data intermediaries to cater in various degrees to producers or consumers. The potential for individualized, personalized pricing is recognized by Shapiro & Varian (1999) and is reviewed in a survey by Fudenberg & Villas-Boas (2012). A recent report by the Council of Economic Advisers (Counc. Econ. Advis. 2015) offers largely negative conclusions regarding consumer welfare.

A recent paper by Dubé & Misra (2017) considers the empirical implications of price discrimination using high-dimensional data from a large, digital firm. The authors run a large, randomized price experiment with a high-dimensional vector of customer features that are observed prior to price quotes. The outcomes of the price experiment are used to train the demand model. They then conduct an optimal third-degree price discrimination exercise on the basis of the observable variables. Already, the optimal uniform price substantially increases profits relative to the current price policy of the firm. They estimate that the third-degree price discrimination policy delivers further increases in the profits without affecting the consumer surplus by much. The social welfare increases as more than two-thirds of the consumers face prices lower than those under the optimal uniform price. By contrast, Shiller (2014) considers personalized pricing in the Netflix environment and finds small incremental gains from using price discrimination that relies on big data.

Dubé et al. (2017) consider the value of one piece of information for targeting policies, namely, the GPS data of a consumer as conveyed by their mobile phone. In a field experiment, they test mobile targeting based on consumers' real-time and historic locations, allowing them to evaluate popular mobile coupon strategies in a competitive market. They find substantial profit gains from price discrimination in a competitive environment.

4.2. Ratchet Effect

The profitability of trading consumer information to facilitate price discrimination raises the issue of the endogenous availability of such information. In particular, information is rarely purchased directly from a consumer in exchange for a monetary payment, a practice far more common in business-to-business transactions. Instead, it is often the case that information must be sourced indirectly by recording the consumer's actions, e.g., their purchase histories. The expected use of this information influences a consumer's willingness to reveal information through their behavior. In other words, ratcheting forces determine the level of the indirect compensation that the consumer requires for the information that they generate.

In the context of price discrimination, such indirect compensation often takes the form of more favorable terms (e.g., a lower purchase price) for transactions that are likely to be recorded and subsequently used against a consumer. For example, a sophisticated consumer may become wary of purchasing unhealthy foods or tobacco products if that information impacts their health insurance premium.[9]

Taylor (2004) develops the first analysis of such a scenario in a two-period model of price discrimination, showing how tracking and selling a consumer's purchase history introduces the need to compensate a sophisticated consumer for their first-period actions. Overall, the transmission of information may benefit a sophisticated consumer while unambiguously hurting a naive consumer. However, even a sophisticated consumer is hurt by any adverse (e.g., discriminatory) use of information that is not collected in the context of a monetary transaction. For example, if a consumer's browsing (not purchasing) history affects future prices, then the scope for compensating them for the data generated is greatly diminished.

Importantly, the compensatory channel is present even if the participating firms do not benefit, on aggregate, from participating in the market for information. Calzolari & Pavan (2006) establish this result in a two-period, two-firm model with general mechanisms, and the example of the data broker in Section 2 uses the intermediary's market power to reach a similar conclusion. Conversely, exogenous (e.g., regulatory) limits to the available contractual instruments may reduce the firms' ability to extract surplus through price discrimination. In this case, the transmission of information can benefit firms and/or consumers.

Along these lines, Bonatti & Cisternas (2018) study how aggregating the information about purchase histories into a consumer score impacts the ratchet effect. They do so in a continuous-time model with a changing consumer type and discriminatory, but linear, prices. Thus, the information environment is high dimensional, as signals arrive dynamically over time. A consumer score is modeled as a linear aggregate of past quantities with exponential decay. One specific instance of a score is given by the posterior mean belief about the consumer's type, given the equilibrium strategy and the entire history of past quantities.

A monopolist data intermediary constructs the consumer score and sells it to a sequence of short-run firms who use it to set prices. As information collection is free, the intermediary is always able to extract a positive price from the sellers. Bonatti & Cisternas (2018) further show that, by increasing the persistence of the consumer's score relative to the Bayesian benchmark, the intermediary is able to mitigate the ratchet effect. This allows them to collect more informative signals from the consumer, which are in turn more valuable for the sellers.

Finally, Ball (2018) also considers a high-dimensional model. In this model, the richness of information is due to the fact that the agent has a multidimensional type vector, yet only one dimension of the type is relevant for the decision maker.

4.3. Ratings, Recommender Systems, and Artificial Intelligence

The sale of consumer scores for marketing purposes is but one instance of markets for aggregated information. For example, consider FICO credit scores for individual consumers and Moody's,

[9]Information about a consumer's preferences may also be used in their favor, e.g., through the customization of product characteristics. De Cornière & de Nijs (2016), Hidir & Vellodi (2018), and Ichihashi (2018) analyze different aspects of the trade-off between content personalization and price discrimination.

Standard & Poor's, or Fitch credit ratings for corporate and sovereign debt. These ratings reduce the high-dimensional information about an entire financial history to a single dimension that facilitates the coordination of actions, such as lending or investment.

More generally, all ratings and recommender systems are means to induce an appropriate course of action. As such, any rating raises the issue of incentive compatibility, as the use of past information determines the rated agent's incentives to undertake specific actions. For example, in the career concerns model of Hörner & Lambert (2017), a rating is used to aggregate a worker's past performance and to convey a productivity estimate (and thus the correct level of pay) to the market. At the same time, ratings are motivational, since they affect the worker's incentives to boost current performance and thus future wages.

Incentive compatibility constraints can also affect the very ability of the market to generate new information. Several online platforms (e.g., the traffic navigation software Waze or the reviews site TripAdvisor) incentivize social experimentation (e.g., trying a new route connecting two points or a new hotel), illustrating how the use of information influences a consumer's incentives to generate data in the first place. Related to this problem, Kremer et al. (2014) and Che & Hörner (2017) analyze the information design problem of a benevolent planner who wishes to induce a sequence of uninformed, short-lived agents to engage in socially useful (but privately costly) experimentation. In the example of navigation software, experimentation entails recommending to some users a route that has not yet been taken. Both of these papers find that commitment power is required to dynamically use past information in a way that makes it worthwhile for consumers to follow the platform's current recommendation.

Recommender systems, as well as analytics services that leverage artificial intelligence (AI), can also be seen as mechanisms for selling information in the form of predictions. Thus, the value of a recommender system can be given in terms of the value added that it contributes to some decision problem. It is thus related to the question of how to measure information (Frankel & Kamenica 2018) and closely related to the optimal pricing of information. On this point, Agrawal et al. (2018) argue that firms that own considerable data on users' preferences online can use AI as a means to sell information indirectly: Instead of distributing unique data sets, providers such as Google, Facebook, Microsoft, and Amazon can bundle a prediction (e.g., consumer *i* is high value for firm *j*) and a product (e.g., an advertising slot or product recommendation).

The distinction between selling information and selling access to a consumer has important implications for the price of information in a dynamic environment. With direct sales of information, buyers can either retain the data, and thus use stale old predictions as an outside option, or hold and retain the original contact. In both cases, the value added of an information seller is to keep the buyer up to date. In particular, as long as the buyer retains the possibility of taking an informed action (e.g., contact a consumer), the data broker will be only able to charge for the innovation component of their data. If, on the contrary, an AI provider offers exclusive access to qualified prospects, they will be able to repeatedly charge for the full (flow) value of their information over time. The potential value of a market for insights—actionable recommendations that do not require distributing raw data—is also discussed by Dahleh (2018).

5. CONCLUSIONS

In this review, we attempt to provide a comprehensive perspective on information markets. At present, far more is known about how to sell a given data set than about how to source data and repackage them as information, e.g., in the form of predictions. Instead of focusing on information acquisition and sales mechanisms separately, however, our perspective emphasizes the critical role of data intermediaries. The data intermediary's central role affords considerable market power. In particular, the ability of the data intermediary to provide terms to both sides of a product market plays a critical role in determining what kind of information gets traded, as well as the welfare and allocative properties of information markets. At the same time, the possible and actual uses of information place severe limits on the acquisition of information by a data broker and on the broker's ability to trade it.

Several crucial questions regarding the development and welfare properties of information markets remain largely open. For instance, what are the dynamics of competition in information provision, and how does competition among heterogeneous data providers enable firms to better segment their customer populations?[10] Relatedly, what are the implications of acquiring an advantage in a downstream market by means of better data (e.g., improvements in the predictive power of an algorithm)?

Similarly, we touch only lightly on the privacy implications of consumer data collection. The structure of markets for information is bound to impact the availability, granularity, and security of individual-level information. In turn, privacy concerns will shape the types of data transactions that take place. We refer the reader to the survey by Acquisti et al. (2016) for a thorough discussion of the economics of privacy.

The market for information is also bound to have implications for industry structure and for the internal organization of production. For example, does the ability to access ever more precise predictions and recommendations (perhaps thanks to competing information providers) shrink the boundaries of the firm and enable a platform model? How does the answer to this question depend on the sensitive nature of the personal data required to formulate accurate predictions?

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