

**Comment of the Global Antitrust Institute,
Antonin Scalia Law School, George Mason University,
on the Canadian Competition Bureau’s White Paper, “Big Data and Innovation:
Implications for Competition Policy in Canada”**

November 17, 2017

This comment is submitted in response to the Canadian Competition Bureau’s White Paper, “Big Data and Innovation: Implications for Competition Policy in Canada.” We appreciate the opportunity to comment, and we commend the Bureau for its commitment to transparency. We submit this comment based upon our extensive experience and expertise in antitrust law, regulation, privacy, and economics.¹

Introduction

The Bureau’s White Paper is careful to offer a balanced economic perspective, discussing both the procompetitive aspects of conduct that involves big data as well as the potential anticompetitive risks. We find it particularly noteworthy what the Bureau does not say; namely, there is no call for new regulations, tools, or standards to assess anticompetitive claims that arise in the context of big data.² We commend the Bureau’s conclusion that existing competition laws grounded in sound economic fundamentals deserve primacy in antitrust analysis in all markets, including those characterized by big data.

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² Similarly, the European Commission, after contemplating new regulations for online platforms, ultimately decided that its existing competition laws are sufficient to deal with platforms. This decision was consistent with the comment that the GAI submitted. See the Global Antitrust Institute (December 29, 2015), “Comment of the Global Antitrust Institute, George Mason University School of Law, on the European Commission’s Public Consultation on the Regulatory Environment for Platforms.”

In this comment, we urge the Bureau to consider expanding the White Paper to address important issues involving the analyses of big data that would be of considerable value to the international antitrust community.

First, we recommend the Bureau significantly expand the discussion regarding big data and entry in Sections III.B (Challenges with assessing market power), III.D.2 (Prevention of competition), and III.D.4 (Dynamic competition and non-price effects). There are several important questions antitrust agencies face in these contexts. While there is a tendency to presume big data gives an incumbent an insurmountable advantage, the advantage, if any will depend on the specifics of the particular industry involved and the level of product differentiation. This is borne out in the history of entry and the disruption that entrants can wreak on incumbents. This naturally leads to the question of whether or not big data should be considered a barrier to entry. We suggest this is not the right question. Rather, the focus should be on the welfare implications of big data.

Second, policy prescriptions involving big data often concern privacy issues.³ It is important, however, that privacy concerns be treated separately from antitrust issues. Some equate data collected from individuals to a “price” they pay for access to free content or a platform, and use this analogy to shoehorn what are really privacy concerns into competition policy. Upon closer inspection, however, the analogy breaks down once one considers that data collection is an investment to improve content and matching, and that consumers have heterogeneous tastes for privacy. Another concern arises because privacy is an inherently subjective value. Vesting antitrust enforcers with discretion to block a transaction or challenge conduct based upon its effect on privacy would introduce a great deal of legal uncertainty concerning antitrust standards, which would reduce incentives to engage in beneficial uses of big data. If transactions or conduct raise privacy concerns, those concerns should be addressed under the appropriate consumer protection laws.

Third, we recommend that the Bureau not take any actions that would hinder companies’ abilities to use big data to engage in differential pricing. Charging different prices based upon estimated willingness to pay is unlikely to have adverse effects on consumers; indeed, it often increases welfare by allowing disadvantaged consumers access to something at an affordable price. Further, differential pricing can spur competition by making additional entry into a market possible, and by allowing firms to target discounts at rivals’ customers.

Finally, the White Paper also clearly addresses the role of firm size in antitrust analysis, an issue with significance beyond big data: “Competition policy in Canada does not, and should not, assume that ‘big is bad.’ Companies that achieve a leading market position—even a dominant one—by virtue of their own investment, ingenuity, and competitive performance should not be penalized for doing so. Imposing a penalty for excellence removes the incentives

³ See FED. TRADE COMM’N, *Big Data: A Tool for Inclusion or Exclusion? Understanding the Issues* (2016).

to pursue excellence.”⁴ This statement is firmly grounded in sound economic research and should be a guiding principle when analyzing topics such as big data.

Big Data and the Production Function

Before assessing how best to evaluate the significance of big data for competition policy, it is worth considering how big data fits into a firm’s overall production process. Clearly, in certain markets, big data represents an important input in the production of a firm’s output. In fact, that output could be considered “big data” in of itself if we consider products such as commercial databases.

The importance of big data will continue to grow as the cost to collect and store large volumes of data continues to fall for both online and offline businesses. For example, a website might track and store every click that its users make while on the website. These data, in turn, could allow the website to better tailor advertisements to a specific user’s interests; determine which features to promote and which features to drop; and improve the overall design of the site. Another example is a grocery store that collects and analyzes transaction data from loyalty card customers. The grocery store could use those data to evaluate the effectiveness of sales and promotions; determine the right mix of products to carry; and optimize its inventory.

As in other areas of business, some firms are more able than others to use and organize assets. Therefore, the value of big data can be unlocked only when combined with other inputs, and firms differ in their ability to do that. The implication is that, when considering the role that big data plays in a given market, rivals might speciously suggest that a market leader is succeeding due to the leader’s sheer volume of data, when it is not data which is scarce but the skill and talent needed to combine the data with other inputs to produce something of value.

Firms are also differentiated in the characteristics of their final product and in the mix of inputs used in their production processes. For instance, an entrant could choose to invest to some degree in big data but not to the extent of an incumbent. Thus, to produce a given level of quality, one firm might use a mix of big data, intellectual property, and highly skilled labor while another firm might achieve a similar level of quality, using the same set of ingredients but in different proportions—relying on its particular comparative advantage.⁵ Demsetz (1982) observed that conditions frequently considered barriers to entry, such as scale economies, capital requirements, and advertising expenditures, are not the fundamental source of barriers;

⁴ See Canadian Competition Bureau, *White Paper on Big Data and Innovation: Implications for competition policy in Canada*, Draft Discussion (2017) at 3.

⁵ See Nils-Peter Schepp & Achim Wambach, *On Big Data and Its Relevance for Market Power Assessment*, 7 J. EUROPEAN COMPETITION L. & PRAC. 120, 122 (2016) (“[P]otential competitors do not necessarily have to build a dataset equivalent to the size of the incumbent . . . They rather need to find ways to accumulate highly relevant data to build a competitive, not necessarily the same dataset.”).

the fundamental barriers are rather the cost of information and the uncertainty that an entrant has to overcome.⁶ In other words, it is not big data *per se* that represents the barrier to entry, but rather what big data helps a firm accomplish. This point is consistent with the observation that, over time, incumbents inevitably change how they combine their various inputs to achieve their levels of output and quality. For instance, an incumbent might have originally entered with a lower cost curve, a superior algorithm, or a valuable patent but, over time, to improve its product, it comes to use big data in greater proportion than when it first entered the market.⁷ Similarly, an entrant might initially operate with “small” or “medium” data but improve quality over time as its installed base of users grows.

The larger point is that the use of big data is, in of itself, not an indication that big data is required to compete effectively. Consequently, for the purpose of competition policy, it is important to consider *why* a product produced with the aid of big data might be successful. For example, network effects could be the primary reason a product is successful in gaining and retaining consumers.⁸ While network effects benefit firms with a large installed base, entrants can and do frequently overcome network effects.⁹ Superior design can also make the difference between a successful product and an unsuccessful one. For example, it could be a superior pricing algorithm and not big data that drives a firm’s comparative advantage. Even if the use of big data is the primary reason for one firm’s success, a relevant question is whether comparable, but not necessarily equivalent, data are costly to acquire. Moreover, is the real difference between two similarly situated firms the relative scarcity of data or their ability to analyze and monetize the data?

Is Big Data an Entry Barrier?

The prior discussion leads naturally to a question of whether big data is itself a barrier to entry. Before addressing this question, it is important to consider how economists define “barriers to entry,” and how this concept relates to the analysis of competitive outcomes.

⁶ Harold Demsetz, *Barriers to Entry*, 72 AM. ECON. REV. 47 (1982).

⁷ An example would be Walmart. Although founded in 1962, today, Walmart analyzes a tremendous amount of data. Walmart currently processes 2.5 petabytes of data from 1 million customers every hour and uses big data to improve operational efficiency and increase online sales. See *How Big Data Analysis Helped Increase Walmart Sales Turnover*, DEZYRE (May 23, 2015), <https://www.dezyre.com/article/how-big-data-analysis-helped-increase-walmarts-sales-turnover/109>; Walmart Staff, *5 Ways Walmart Uses Big Data to Help Customers*, WALMART TODAY (Aug. 7, 2017), <https://blog.walmart.com/innovation/20170807/5-ways-walmart-uses-big-data-to-help-customers>.

⁸ While big data and network effects are often discussed jointly and perhaps interchangeably, they are distinct concepts. Although big data can have positive feedback effects – which is a type of network effect – it can be quite weak.

⁹ See discussion *infra* at “History of Entry” pp. 7-9.

Bain (1956) defined barriers to entry as structural factors that allow incumbents to persistently price above the competitive level without the threat of entry.¹⁰ Examples include economies of scale that require large capital expenditures, product differentiation, and absolute cost advantages. Stigler (1968) considered barriers to entry as costs that an entrant must incur but that incumbents do not.¹¹ Examples include patents and grandfathered government regulations but not economies of scale to the extent that an entrant has access to the same cost function. The appeal of Stigler's definition is its recognition that incumbents can earn supra-normal profits over the long-term only if they have some persistent advantage over potential rivals. What is missing from both Bain and Stigler, however, is an assessment of welfare. Both Fisher (1979) and von Weizsäcker (1980) filled this void with a normative definition that incorporates social welfare.¹² Fisher found "a barrier to entry exists when entry would be socially beneficial but is somehow prevented."¹³ von Weizsäcker stated, "a barrier to entry is a cost of producing which must be borne by a firm which seeks to enter an industry but is not borne by firms already in the industry and which implies a distortion in the allocation of resources from the social point of view."¹⁴ If economies of scale can increase overall welfare *and* we associate entry barriers with inefficiencies, then, von Weizsäcker asks, "in which sense can we speak of a barrier to entry?"¹⁵ Thus, according to Fisher, "the right issue is not whether there are barriers to entry into the production of a particular mousetrap, but whether there are barriers to entry into innovation in mousetraps."¹⁶ In other words, it is not the input itself that is the barrier to entry but, if they exist, hindrances to obtaining and utilizing the inputs, which incumbents do not face.

The tension in defining barriers to entry is that there are really two ways in which the term is discussed. As Carlton stated, "Trying to use 'barriers to entry' to refer to both the factors that influence the time it takes to reach a new equilibrium and to whether there are

¹⁰ See JOSEPH BAIN, BARRIERS TO NEW COMPETITION 3 (1956).

¹¹ See GEORGE J. STIGLER, THE ORGANIZATION OF INDUSTRY 67 (1983) ("A barrier to entry may be defined as a cost of producing (at some or every rate of output) which must be borne by a firm which seeks to enter an industry but is not borne by firms already in the industry.").

¹² Franklin M. Fisher, *Diagnosing Monopoly*, 19 Q. REV. ECON. & BUS. 7 (1979); C.C. von Weizsäcker, *A Welfare Analysis of Barriers to Entry*, 11 THE BELL J. ECON. 399 (1980).

¹³ Fisher, *supra* note 12, at 23.

¹⁴ C.C. von Weizsäcker, *supra* note 12, at 400.

¹⁵ *Id.* at 401.

¹⁶ Fisher, *supra* note 12, at 27.

excess long-run profits is confusing.”¹⁷ Therefore, for the purpose of competition policy, Carlton recommends that “rather than focusing on whether an entry barrier exists according to some definition, analysts should explain how the industry will behave over the next several years ... [which] will force them to pay attention to uncertainty and adjustment costs.”¹⁸

Consequently, we recommend that the Bureau avoid suggesting that big data is or is not a barrier to entry but rather to use its White Paper as an opportunity to properly frame the economic issues arising with big data as one potential factor when examining “the timeliness, likelihood, and sufficiency of entry efforts an entrant might practically employ.”¹⁹ There are clearly impediments that an entrant must overcome in order to compete effectively. Common examples include regulatory compliance costs, expenditures on specialized equipment, and hiring skilled labor. Some obstacles are nominal. Some obstacles are substantial. Attempting to classify these impediments as entry barriers or not creates the conflation mentioned by Carlton. If this classification exercise is undertaken, however, it is important to clarify whether the discussion is in regards to the time required to reach a new equilibrium or whether it is in regards to a cost that is preventing socially desirable entry.

It is also relevant to note that big data is not an exogenous factor that dictates the number of firms in a market, which in turn determines the degree of competition and the rate of return. This contrary view is a vestige of the discarded structure-conduct-performance paradigm. Rather big data is endogenous, as are other dimensions of non-price competition.²⁰ For instance, if a firm invests heavily in research and development, which allows it to introduce a new product or substantially to improve an existing product, we would not normally view this as anticompetitive conduct or even conduct that ultimately leads to anticompetitive results. Rather, we would consider investment in innovation to be procompetitive. Similarly, investments in big data can create competitive distance between a firm and its rivals, including potential entrants, but this distance is the result of an activity that antitrust laws should encourage, not penalize.²¹ Moreover, the observation that a firm is making large margins gives

¹⁷ Dennis W. Carlton, *Barriers to Entry*, 1 ISSUES IN COMPETITION L. & POL’Y 601, 606 (2008).

¹⁸ *Id.* at 615.

¹⁹ U.S. DEP’T OF JUSTICE & FED. TRADE COMM’N, HORIZONTAL MERGER GUIDELINES § 9 (2010).

²⁰ See Carlton *supra* note 16, at 604 (“Models that focus on only price competition may fail miserably to correctly predict industry concentration and consumer welfare when there are other product dimensions along which competition occurs. This is likely to be particularly true in industries requiring investment and creation of new products.”).

²¹ The Bureau’s White Paper makes this precise point at 14: “Developing valuable data through competition on the merits does not run afoul of the Act even if it results in significant market power. For example, a firm can create market power by developing a high-quality product or an efficient production process[.]”

no indication whether this represents supra-competitive pricing if we properly consider the rate of return required over the whole process including the investment costs into big data.²²

Even if big data represents an important component in the success of an incumbent, entrants can differentiate their products along other dimensions important to consumers. For instance, a grocery store entrant might focus more on carrying locally made produce or products that cater to specific diets. An online firm might focus more on building network effects or greater integration with complementary products rather than the use of big data. As Tucker and Wellford state, “The fact that some established online firms collect a large volume of data from their customers or other sources does not mean that new entrants must have the same quantity or type of data in order to enter and compete effectively ... [L]ack of asset equivalence should not be a sufficient basis to define a barrier to entry.”²³

History of Entry

In assessing the prospect of entry into any given market, an important consideration is the actual history of entry in that market.²⁴ The evidentiary value of prior instances of entry, however, depends upon the extent to which current entry conditions are similar to prior entry conditions. The fact that entry occurred previously does not establish that entry is currently easy. On the other hand, one has to be cautious before inferring that long periods without entry implies there are substantial barriers to entry. Rather, the lack of entry could reflect a competitive market where the economic profits are not sufficiently high to induce entry.

With these caveats in mind, in the table below, we highlight some recent entry episodes, where the entrants successfully overtook incumbents with arguably big data advantages.²⁵

²² Michael L. Katz & Carl Shapiro, *Systems Competition and Network Effects*, 8 J. ECON. PERSPECTIVES 93, 107 (1994) (“[M]erely observing a firm with a position of market dominance does not imply that the firm is earning super-normal profits: the firm’s quasi-rents may merely reflect costs incurred earlier to obtain the position of market leadership.”).

²³ Darren S. Tucker & Hill B. Wellford, *Big Mistakes Regarding Big Data*, ANTITRUST SOURCE, Dec. 2014, at 1, 7.

²⁴ See U.S. DEP’T OF JUSTICE & FED. TRADE COMM’N, HORIZONTAL MERGER GUIDELINES § 9 (2010) at 38 (“The Agencies consider the actual history of entry into the relevant market and give substantial weight to this evidence.”).

²⁵ The presumption that incumbents’ possession of big data results in insurmountable and inefficient barriers to entry harkens to a parallel presumption that inferior standards become locked-in due to network effects. This presumption was dispelled through the work of economists Stan J. Liebowitz and Stephen E. Margolis. In their article, “The Fable of the Keys,” Liebowitz and Margolis document how the QWERTY keyboard standard is equal to, if not better than, the rival Dvorak keyboard, despite the conventional perception that QWERTY was markedly inferior and only obtained market leadership due

Incumbent	Disruptors
Myspace, Friendster	Facebook
Taxi Cabs	Uber
iTunes	Spotify, Amazon Music, TIDAL
Yahoo, AltaVista	Google

While the examples of Google disrupting Yahoo and Facebook disrupting MySpace are well-documented, they are far from the only instances of an incumbent with a seemingly significant big data advantage losing market share to a newcomer.

Apple's iTunes is an example of a powerful incumbent that was overtaken in the market by a newcomer. Started in 2001, iTunes sold digital copies of songs, and eventually audiobooks, eBooks, movies, and television shows.²⁶ By 2010, Apple's iTunes had roughly 70 percent of US online music market.²⁷ With years in the market, along with the massive sales of Apple iPhones, iPods and Mac computers, the company inevitably amassed large amounts of data. That, however, did not stop Spotify from entering the market in 2008. Spotify changed the online music industry by offering a music streaming service, where customers could listen free of charge with advertisements or pay for a premium service with the ability to download songs and make their own playlists. Spotify's pivot toward streaming services, in addition to the ability to download songs, has caused other major players to launch similar services. Apple has released Apple Music and Amazon has launched Amazon Music to compete with the Spotify. Despite being a newcomer in the market, and taking on the incumbent Apple, Spotify currently has the largest number of users, and experts are placing a \$16 billion-dollar valuation on the company.²⁸

Chiou and Tucker find little empirical evidence that the possession of historical data provides an advantage to firms, in terms of their market shares.²⁹ As Schepp and Wambach state, "The origin of many innovative start-ups illustrates that companies with smaller but

to network effects. See Stan J. Liebowitz & Stephen E. Margolis, *The Fable of the Keys*, 30 J.L. & ECON. 1 (1990). The authors also examine how the actual evidence diverges from the conventional perceptions associated with other perceived market failures including the VHS versus Beta standard for video recorders. See STAN J. LIEBOWITZ & STEPHEN E. MARGOLIS, WINNERS, LOSERS & MICROSOFT, COMPETITION AND ANTITRUST IN HIGH TECHNOLOGY (1999).

²⁶ Mike Harvey, *Apple Investigated*, THE TIMES (May 27, 2010).

²⁷ *Id.*

²⁸ Sophie Sassard *et al.*, *Exclusive: Spotify's Valuation Turned Up to \$16 billion in Private Trades – Sources*, REUTERS (Sept. 27, 2017).

²⁹ Leslie Chiou & Catherine Tucker (2017), *Search Engines and Data Retention: Implications for Privacy and Antitrust*, NBER Working Paper No. 23815.

possibly more specialized datasets and analytical expertise may be able to challenge established companies.”³⁰

Finally, big data is often invoked for the online sector, yet one of the defining features of the online sector is that entrants can first enter and *then* obtain the data once the service is operational. As Tucker and Wellford state, “Entering the market and then collecting and analyzing user data is not a theoretical approach but rather the very model followed by many of the leading online firms when they were startups or virtual unknowns, including Google, Facebook, Yelp, Amazon, eBay, Pinterest, and Twitter.”³¹

Privacy

The Bureau should cabin privacy from antitrust discussions. Antitrust’s sole focus on competition has served consumers well, and integrating subjective notions like privacy into antitrust would be a mistake on a number of grounds.³² First, it ignores the benefits built into new uses of data. To see how the analogy between privacy and quality begins to break down, consider the manufacturer that exercises market power by skimping on quality in order to pad profits. Why do profits increase when, for example, a cookie maker uses less sugar or inferior cocoa powder, or an automobile manufacturer uses low quality paint or electronics? *Ceteris paribus*, profits rise because inferior inputs tend to mean lower costs. In this manner, a reduction in quality with the price held constant is analogous to an increase in price. Contrast this situation with an online publisher that decides to collect and mine additional consumer data. Distinct from the reduction in quality scenarios above, the online publisher does not profit automatically by reducing consumer privacy. Taking additional consumer data is not the same as skimping on quality, because collecting, storing, and analyzing data is an *additional cost* incurred to improve revenue through better matching of content and ads to consumers. With heterogeneous consumer preferences for privacy, this data collection leads to net benefits to some, and net costs to others. In this manner, data cannot be analogized to an increase in price.

Differential Pricing

The Bureau should also resist calls to treat differential pricing from big data classifications as a privacy issue. Big data stands to provide tremendous marketplace benefits by reducing asymmetric information; problems of “adverse selection” and “moral hazard”

³⁰ Nils-Peter Schepp & Achim Wambach, *On Big Data and Its Relevance for Market Power Assessment*, 7 J. EUROPEAN COMPETITION L. & PRAC. 120, 122 (2016).

³¹ Tucker & Wellford, *supra* note 23, at 7.

³² See James C. Cooper, *Privacy and Antitrust: Underpants Gnomes, The First Amendment, and Subjectivity*, 20 GEO. MASON L. REV. 1129 (2013).

impose real costs on the economy.³³ One area of specific interest has been the use of big data to engage in price discrimination, or what is also referred to as differential pricing.³⁴ As discussed in detail below, economic analysis suggests that restrictions on the ability of firms to use big data to tailor consumer prices are likely to reduce welfare.

Differential pricing comes in three varieties: first-, second-, and third-degree. First-degree discrimination is often referred to as “perfect” differential pricing, as it involves a firm charging each consumer his or her exact willingness to pay. Given the large data demands of engaging in first-degree discrimination, firms instead rely chiefly on less fine market segmentations, either by allowing consumers to self-select based on non-linear pricing schemes or product attributes (second-degree), or by segmenting markets using observable characteristics, such as age, as proxies for willingness to pay (third-degree).

First-degree differential pricing unambiguously increases total welfare because it expands output; consumers whose willingness to pay fell below the uniform price, but above the marginal cost of production, were priced out of the market but are able to participate at lower prices.³⁵ Although the welfare effects of second- and third-degree differential pricing are indeterminate theoretically, empirical evidence suggests that their use can be welfare-enhancing.³⁶ Moreover, U.S. antitrust authorities have taken the position that differential pricing is unlikely to pose a threat to consumer welfare. For example, neither the Federal Trade Commission nor the Department of Justice has challenged differential pricing in decades,³⁷ and the Department of Justice sided with the defendant in the most recent Robinson-Patman case

³³ See James C. Cooper, *Separation, Pooling, and Predictive Privacy Harms from Big Data: Confusing Benefits for Costs?* 15-32 (Geo. Mason L. & Econ., Res. Paper No. 15-32, 2015).

³⁴ See, e.g., Ryan Calo, *Digital Market Manipulation*, 82 GEO. WASH. L. REV. 995, 1029-30 (2014) (firms will use big data to charge consumers “as much as possible” and to manipulate them to buy products and services that they “[do] not need or need[] less of.”); Jennifer Valentino-DeVries *et al.*, *Websites Vary Prices, Deals Based on Users’ Information*, WALL ST. J. (Dec. 24, 2012), <http://www.wsj.com/articles/SB10001424127887323777204578189391813881534> (finding that differential online pricing based on zip code leads to those in relatively poorer zip codes to pay more).

³⁵ First-degree differential pricing is welfare-reducing only if the welfare gains from increased output are less than the informational and implementation costs associated with differential pricing. See, e.g., Jack Hirshleifer, *The Private and Social Value of Information and the Reward to Inventive Activity*, 61 AM. ECON. REV. 561 (1971).

³⁶ See, e.g., Igal Hendel & Aviv Nevo, *Intertemporal Differential Pricing in Storable Goods Markets*, 103 AM. ECON. REV. 2722 (2013); Phillip Leslie, *Differential Pricing in Broadway Theatre*, 35 RAND J. ECON. 520 (2004); Andrew Cohen, *Package Size and Differential Pricing in the Paper Towel Market*, 26 INT. J. INDUS. ORG. 502 (2008).

³⁷ See ANTITRUST MODERNIZATION COMM’N, REPORT & RECOMMENDATIONS 318 (2007).

heard by the Supreme Court, arguing that a ban on differential pricing was likely to harm competition.³⁸ Indeed, the bi-partisan Antitrust Modernization Commission concluded that the U.S. law prohibiting differential pricing should be repealed because it could not be reconciled “with the basic purpose of antitrust laws to protect competition and consumer welfare.”³⁹

When considering regulation of the ability of firms to use consumer data to charge consumers different prices, three points deserve consideration. First, as we move from a world in which firms rely on crude proxies for willingness to pay—age, income, purchase of complementary goods, *et cetera*—towards more granular targeted pricing, we begin to move toward a world of first-degree differential pricing, which, as discussed above, unambiguously expands the number of consumers who can participate in the market.⁴⁰

Second, there are likely to be improvements in income distribution from more granular dynamic pricing. If a firm can segment markets, optimal pricing requires the market with the most elastic demand to pay the lowest prices.⁴¹ Because price elasticity of demand is a negative function of income, a firm that segments its market into rich and poor consumers would charge a higher price to the former and lower one to the latter.⁴² Indeed, one of the few public attempts at dynamic pricing involved Orbitz placing higher-priced hotels more prominently in search results for Mac users under the assumption that Mac users typically are wealthier than PC users.⁴³

³⁸ See Brief for the United States as Amicus Curiae Supporting Petitioner at 27 & n.15, *Volvo Trucks N. Am., Inc. v. Reeder-Simco GMC, Inc.*, 544 U.S. 164 (2006) (No. 04-905) (“Imposing liability for differences in concessions offered to dealers bidding on different sales would limit suppliers’ ability to tailor prices to the competitive situation, and thus diminish the vigor of interbrand price competition.”).

³⁹ ANTITRUST MODERNIZATION, *supra* note 37, at 322.

⁴⁰ This effect is analogous to that recognized by Strahilevitz in conjunction with statistical discrimination. Lior Jacob Strahilevitz, *Privacy versus Antidiscrimination*, 75 U. CHI. L. REV. 363 (2008). Strahilevitz argues that as we move from a world in which parties use protected classes as crude proxies for undesirable economic characteristics to one in which they can measure undesirable economic characteristics directly, statistical discrimination is likely to decline. *Id.* at 364, 371.

⁴¹ This is called Ramsey pricing, and formally requires: $\frac{P_A}{P_B} = \frac{1 + \frac{1}{\varepsilon_A}}{1 + \frac{1}{\varepsilon_B}}$, where ε_i is the own-price elasticity of demand for good i .

⁴² For example, students and the elderly are often offered discounts at movies and restaurants. Further, studies show that the poor respond to excise taxes on cigarettes and alcohol by curtailing their consumption more than the rich. See, e.g., Michael Grossman, Frank J. Chaloupka & Richard Anderson, *A Survey of Economic Models of Addictive Behavior*, 28 J. DRUG ISSUES 631, 635 (1998).

⁴³ This instance was not really differential pricing because the Mac users were charged the same prices as PC users for the same hotel. More expensive hotels were just more prominently placed for the Mac

Finally, it is important to note that differential pricing does not occur in a vacuum. Although firms rationally may seek to extract as much surplus as they can from consumers, they are limited in this quest by the fact that in most markets several other firms are trying to accomplish the same thing. To the extent that big data allows firms in a market to target their rivals' customers, it can intensify competition by allowing firms to compete for *each* consumer. In this manner, differential pricing can lead to lower prices for *all* consumers.⁴⁴ As such, restrictions on the ability to tailor prices to consumer demand actually would deprive consumers of the benefits of more robust competition.

Conclusion

The Canadian White Paper offers a balanced view of big data. In doing so, it avoids calls for new regulations or calls to move away from sound economic fundamentals. This is a policy achievement, in of itself. Continuing on the theme of sound economic fundamentals, we respectfully recommend that the Bureau consider expanding its discussion of big data as a barrier to entry. As we detail in this commentary, the economic concept of barriers to entry can create some degree of confusion given its use to describe both the existence of socially undesirable, long-run, supra-competitive profits and its use in competition policy to address factors that impact the timeliness, likelihood, and sufficiency of entry. Consequently, we suggest avoiding the classification of big data as a barrier to entry. At the very least, it must be made abundantly clear, how the term is being used.

We appreciate the opportunity to comment and would be happy to respond to questions the Canadian Competition Bureau may have regarding this comment.

users. Dana Mattioli, *On Orbitz, Mac Users Steered to Pricier Hotels*, WALL ST. J. (Aug, 23, 2012), <http://www.wsj.com/articles/SB10001424052702304458604577488822667325882>.

⁴⁴ See Lars A. Stole, *Differential Pricing & Competition*, in 3 HANDBOOK OF INDUSTRIAL ORGANIZATION 2221 (2007); Kenneth S. Corts, *Third Degree Differential Pricing in Oligopoly: All-Out Competition and Strategic Commitment*, 29 RAND J. ECON. 306 (1998); Jacques-Francois Thisse & Xavier Vives, *On the Strategic Choice of Spatial Price Policy*, 78 AM. ECON. REV. 122 (1988). See also James C. Cooper et al., *Does Differential Pricing Intensify Competition? Implications for Antitrust*, 72 ANTITRUST L.J. 327 (2005).