



HAL
open science

Digital Platforms Strategies and Regulation: Essays in Industrial Organization

Pierre-François Darlas

► **To cite this version:**

Pierre-François Darlas. Digital Platforms Strategies and Regulation: Essays in Industrial Organization. Economics and Finance. Institut Polytechnique de Paris, 2024. English. NNT : 2024IPPAT035 . tel-04957492

HAL Id: tel-04957492

<https://theses.hal.science/tel-04957492v1>

Submitted on 19 Feb 2025

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



INSTITUT
POLYTECHNIQUE
DE PARIS

NNT : 2024IPPAT035

Thèse de doctorat



Digital Platforms' Strategies and Regulation: Essays in Industrial Organization

Thèse de doctorat de l'Institut Polytechnique de Paris
préparée à Télécom Paris

École doctorale n°626 École doctorale de l'Institut Polytechnique de Paris
(ED IP Paris)

Spécialité de doctorat : Sciences Économiques

Thèse présentée et soutenue à Palaiseau, le 3 décembre 2024, par

PIERRE-FRANÇOIS DARLAS

Composition du Jury :

Thibaud Vergé Vice-président, Autorité de la concurrence	Président Examinateur
Alexandre de Cornière Professeur d'Économie, Toulouse School of Economics	Rapporteur
Axel Gautier Professeur d'Économie, HEC Liège	Rapporteur
Grazia Cecere Professeure d'Économie, IMT Business School	Examinatrice
Marc Bourreau Professeur d'Économie, Télécom Paris	Directeur de thèse
Marie-Laure Allain Professeure d'Économie, École Polytechnique - Crest, CNRS	Co-directrice de thèse

Acknowledgements

I would like to express my gratitude to everyone who supported and accompanied me throughout the journey of pursuing and completing this doctoral thesis.

First and foremost, I want to express my deepest gratitude to my thesis supervisors, Marie-Laure Allain and Marc Bourreau, for their invaluable guidance, availability, and patience. From beginning to end, they ensured that my PhD experience was as smooth as possible, allowing me the time and space to focus on my research. I recognize how fortunate I was to benefit from such supportive working conditions—both materially and immaterially—especially in an academic context where this is not always the case. For all this and more, I sincerely thank you.

I am very grateful to the members of my committee, Thibaud Vergé, Alexandre de Cornière, Axel Gautier, and Grazia Cecere, for accepting to be part of my jury. I sincerely appreciate their insightful comments, both during my defense and throughout my PhD. I would also like to thank Laurent Linnemer for his valuable feedback during my mid-term defenses.

Of course, I also want to thank my family for their support whenever I needed it. I am deeply grateful to my parents, who taught my sisters and me many things—most notably, to nurture our curiosity. I also want to thank my two sisters for putting up with their little brother all these years and for shaping my personality, perhaps more than they realize.

Over the four years of my PhD, I was fortunate to learn from many inspiring people. I am deeply grateful for the invaluable feedback I received from faculty members at Télécom Paris, including Michelangelo Rossi, Michele Fabi, David Bounie, José-Luis Moraga Gonzáles, Patrick Waelbroeck, Ulrich Laitenberger, Maya Bacache, Laurie Ciaramella, and Lukasz Grzybowski.

I also cherish the moments shared with my fellow PhD students and postdocs in the department: Adrien Raizonville, Angela Muñoz, Enrick Arnaud-Joufray, Francisco Magalhães Barros, Julien Monardo, Clément Le Ludec, Ivan Shchapov, Chloé Breton, Quentin Durand, Leonardo Leone, Martin Delville, Jean-Baptiste Guiffard, Felix Schleef, and Joshua Brand. Additionally, I am grateful to the dedicated visiting PhD students we had the pleasure of welcoming, Federico Navarra and Luca Rossi, as well as the Young Economist Seminar audience for their insightful discussions.

My sincere thanks also go to the department's administrative personnel for their efforts in ensuring a smooth experience, and to the union representatives I had the opportunity to work with for their commitment to preserving and improving PhD students' working conditions. Lastly, I am grateful to my colleagues at Arcep for warmly welcoming me, being so understanding, and teaching me a great deal during the final months of my PhD.

I was incredibly fortunate to work with Louis Pape, who taught me so much. Beyond being a brilliant economist, he is also an exceptionally kind person, and I am truly grateful to him for everything—including simply being who he is.

I also want to thank Chiara Belletti and Guillaume Thébaudin, with whom I shared most of this journey. They turned it into a joyful experience, not least by helping transform an econ department into a kindergarten from time to time.

Throughout these four years, I was lucky to be surrounded by wonderful friends—Anne, Jules, Laura, Manu, Pablo, Antoine, Gabriel, Céline, Alice, Chloé, Mathurin, Soline, Raphael, Paul, Ugo, Eudes, Constant, Guillaume, Pierre, and Alexandre. Thank you not only for your support but, more importantly, for the much-needed distractions you provided along the way

Lastly, I want to once again express my deep gratitude to my partner, Sonia, for her patience, unwavering support, and for always being so funny, sweet, and radiant.

Contents

Introduction	7
1 Digital Platforms	8
2 Platforms market power and (mis)behavior	13
3 Thesis Contributions	15
1 Digital Business Models and Quality Investment	21
1 Introduction	21
2 The model	24
3 Pricing and investment decisions	26
4 Business model decisions	36
5 Discussion: Market power in the adtech sector	39
6 Conclusion	40
7 Appendices	42
2 Vertical Integration in Online Display Advertising, <i>AdTech</i> Contestability, and Advertising Restrictions	51
1 Introduction	51
2 Model set-up	55
3 Separated <i>adtech</i> stack incumbent	59
4 Integrated <i>adtech</i> stack incumbent	67
5 Robustness checks	77
6 Extension: Capping advertising levels	78
7 Conclusion	81
8 Appendix A	83
9 Appendix B	89
10 Appendix C	92
3 Platform Information Provision : Evidence from an Online Auction Platform	95
1 Introduction	95
2 Research Setting	99

3	Empirical Strategy	104
4	Main Results	109
5	Economic Mechanisms	115
6	Conclusion	117
7	Appendices	119
	Conclusion	139
	Bibliography	143
	Résumé en français	157

Introduction

The emergence and improvement of digital technologies have completely transformed the way people interact, work, relax, travel, and more. New markets, products, uses, customs, and habits have arisen thanks to digital platforms and their users. Major players like Google, Apple, Meta, Amazon, and Microsoft, as well as smaller ones like Airbnb, Uber, and Vinted, have capitalized on the cost reductions enabled by digitization to create and extract value (Goldfarb and Tucker, 2019). They have positioned themselves as intermediaries, using various tools to shape our interactions. For example, Airbnb revolutionized the short-term rental industry, Uber upset the mobility industry, Doctolib transformed the practice of physicians, and so on. Many organizations depend heavily on these firms¹, making them very powerful. Consequently, it is crucial to ensure that these firms' actions align with the public interest.

However, the current state of the digital economy raises some concerns. Indeed, it appears that the markets in which digital platforms operate are highly concentrated (Scott Morton et al., 2019). Academics have extensively studied and debated the significant market power of these firms (Calvano and Polo, 2021), their wide array of pricing (Rochet and Tirole, 2003; Armstrong, 2006) and non-pricing tools (Bourreau and Gaudin, 2022a; Teh and Wright, 2022), and their strong tendency to expand both vertically and horizontally (Gautier and Lamesch, 2021), which creates opportunities for misconduct and anti-competitive practices. Reports from leading experts and institutions have highlighted the limitations of current competition law in addressing and preventing anti-competitive practices by digital platforms (Cr mer, de Montjoye and Schweitzer, 2019; Scott Morton et al., 2019; Furman et al., 2019). Consequently, it is argued that there may be a need for competition policy to adapt, as well as for *ex-ante* regulation. The Digital Markets Act (DMA)², which became applicable in the European Union on May 2, 2024, follows some of these recommendations.³ Given the rapid pace of evolution in digital industries, it seems likely that the scope and the obligations included in the DMA

¹As exemplified by the impact of the CrowdStrike/Windows bug on July 19, 2024, which caused malfunctions in hospitals, airports, and stock exchanges.

²Available at: <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:32022R1925>.

³The DMA provides the European Commission with new tools to ban practices deemed anti-competitive when undertaken by *gatekeepers*. It also addresses issues related to merger control, as Article 14 of the DMA requires gatekeepers to notify the Commission of all intended acquisitions for potential review.

will be updated in the future.⁴

This doctoral thesis seeks to identify and understand the strategies of digital platforms and their impact on market outcomes. Drawing on theoretical and empirical industrial organization, I aim to provide insights that will help policymakers make better decisions in digital contexts.

1 Digital Platforms

1.1 Definition

Belleflamme and Peitz (2021) provide a general definition of platforms, describing them as entities that must bring together economic agents linked by some form of network effects and actively manage these effects. *Digital* platforms are platforms that rely on a technological interface to bring users together.

Network effects exist when the value an economic agent places on a product or a service depends on the number of other people using the same product or service (Rohlf, 1974; Katz and Shapiro, 1985). These effects can be direct (or within-group); for example, on YouTube, viewers may value the comments posted by other viewers below a video, and their valuation of YouTube will increase with the number of other viewers. Maybe more importantly, network effects can be indirect (or cross-group), such as when viewers value the contributions of content creators. As a result, their valuation of YouTube will also increase with the number of content creators. However, network effects can also negatively impact users. For instance, on YouTube, advertisers exert a negative cross-group externality on viewers.

Seminal works by Rochet and Tirole (2003), Caillaud and Jullien (2003), Anderson and Coate (2005), and Armstrong (2006) have contributed to the formal analysis of platform economics, paving the way for a broad body of literature on platform markets.

1.2 Platforms' business models

A platform can emerge and be sustainable as long as it is able to create and extract value. This depends in particular on its ability to successfully solve Caillaud and Jullien (2003)'s *Chicken-and-egg* problem and bring groups of users together. To achieve this, it can employ various strategies, such as a *divide-and-conquer*⁵ strategy or a seeding⁶ strategy (Belleflamme and Peitz, 2021). A platform's ability to create value comes from its capacity to partially internalize network externalities. It is crucial that platforms max-

⁴Article 53 of the Digital Markets Act states that the regulation shall be evaluated every 3 years, as well as potentially be modified.

⁵Which involves subsidizing one side while charging another profit-making one.

⁶Which involves attracting sides sequentially, starting as a pure reseller, like Amazon, for instance.

imize these externalities by leveraging their technological interface to make information more accessible, reduce search and transaction costs. Value extraction is determined by the price structure, which is of critical importance in platform markets. Indeed, prices can be asymmetric, Rochet and Tirole (2006) even define a market as two-sided if “the platform can affect the volume of transactions by charging more to one side of the market and reducing the price paid by the other side by an equal amount; in other words, the price structure matters, and platforms must design it so as to bring both sides on board”.

Platforms decide which groups of users to include⁷ and set their price structure, thereby defining their monetization strategy and business model (Rysman, 2009). To achieve market efficiency, platforms can adopt various business models. For example, they may charge both sides an access fee, as seen with video game consoles, or offer free access to one side in exchange for their attention or personal data, which is ultimately sold to advertisers or data brokers. The digital economy and digital platforms have been crucial in the development of new business models.

1.3 Platforms design

To position themselves as efficient intermediaries, platforms must make decisions on various aspects of their design, rules, and pricing, each of which has substantial implications for the market and its participants. Once they have acquired this role, they “act as regulators” of interactions between their users (Boudreau, 2009). A platform can make a wide variety of design decisions (Hagiu and Wright, 2015). It may decide who is allowed to access it; for example, most social media platforms like Instagram, Facebook, Reddit, and Twitter require users to be at least 13 years old. Apps available on the Apple Store must be approved by the platform, unlike those on the Google Play Store. Platforms can also shape the nature of the interactions they permit. For instance, dating apps like Tinder and Hinge do not allow users to send pictures to each other through the built-in messaging system. Platforms can engage in various forms of content moderation and limit user expression, as exemplified by social media and video platforms like Twitter, YouTube or Twitch (Liu, Yildirim and Zhang, 2022; Madio and Quinn, 2024). Various design choices made by platforms can also have significant implications. For instance, they can decide how to organize information (Hunold, Kesler and Laitenberger, 2020*a*) or how to construct their recommendations, whether algorithmic or not (Aguiar and Waldfogel, 2021). These decisions greatly influence the visibility and ultimately the success of certain products and/or users on the platform. Other examples of choices made by platforms to address problems of information asymmetry include the design of reputation systems. Platforms can gather and aggregate extensive data to inform their users, but

⁷For instance, a marketplace like Vinted, which matches buyers and sellers, can decide to include advertisers as an additional side or not.

the design of these systems can have significantly different implications, as they may fail to promote the highest quality users (Cai et al., 2014). Policies regarding the disclosure of private information can also vary significantly across platforms. Platforms may choose to mandate the disclosure of information such as identity, location, etc., and then reveal it to other users, which could expose participants to discrimination (Edelman, Luca and Svirsky, 2017). Similarly, a platform’s decision on how costly it is for users to acquire information can lead to similar discriminatory behaviors (Manant, Pajak and Soulié, 2019).

We have seen that platforms have the ability to decide and influence greatly the nature of their users’ interactions and even have an impact on society as a whole. However, it is important to keep in mind that these platforms, as private firms, behave in a profit-maximizing way. This implies, that there could be some legitimate concerns about their incentives being misaligned with those of a welfare-maximizing social planner (Teh, 2022).

1.4 Concentration and market power in digital markets

I have previously emphasized the omnipresence of platforms in individuals’ daily lives and their influential role as regulators of interactions. This raises concerns about potential deviations from the social optimum. Numerous reports and studies highlight the high levels of concentration in the markets where platforms operate (Scott Morton et al., 2019; Crémer, de Montjoye and Schweitzer, 2019; Competition and Markets Authority, 2020). This may not be entirely surprising or necessarily the result of “monopolization,” as many of their intrinsic characteristics could naturally lead to such situations.

1.4.1 Sources of concentration

There are multiple factors that can lead to high levels of concentration in digital markets. I will briefly outline some of these factors before discussing those that may mitigate the trend toward concentration.

Economies of scale. Digital platforms have emerged due to advancements in technologies such as the Internet. These platforms naturally benefit from the features of these technologies, leading to economies of scale. Digital industries are characterized by high fixed costs and low variable costs (Shapiro, 1999). For example, developing a website, an algorithm, or a technology requires investments that do not necessarily depend on the number of users served. The digital medium allows for low replication costs (Varian, Farrell and Shapiro, 2004; Goldfarb and Tucker, 2019), further accentuating the increasing returns to scale in digital industries. This creates a natural source of market concentration, as the substantial investments required can represent significant barriers to entry for new firms and platforms.

Network effects. As discussed previously, network effects play a crucial role in the study of platforms. They are fundamental to value creation for these firms and are also a source of market concentration. Since network effects influence the perceived value of a service—enhancing it as the number of users increases—they create a size advantage, and even lead the market to tip (Arthur, 1989). Users may prefer to converge on the same platform due to direct or indirect network effects, creating a “winner-takes-all” dynamic that favors the emergence of a dominant platform (or network). Moreover, user beliefs about networks sizes can play a role and protect the incumbent from competition due to market *focality* (Halaburda and Yehezkel, 2019; Halaburda, Jullien and Yehezkel, 2020).

The role of data. The business model of many platforms relies heavily on exploiting data. Successful platforms like Facebook, Booking.com, Spotify, and Google collect, process, organize, and/or monetize data. Whether it is to address information asymmetries, build recommendation algorithms, or sell information about their users, the more data platforms can obtain, the better they become at achieving their objectives. Moreover, data usage can allow some increasing return to scale to materialize (Hagiu and Wright, 2023). Additionally, the issue may not only be the quantity of data a new platform lacks but the absence of any data at all. Access to certain user information may be restricted, preventing the emergence of new players.⁸ Data may constitute an essential facility, and the lack of data sharing between competing platforms can contribute to market concentration.⁹

The market characteristics described above can create a trend toward the emergence of a dominant platform. Platforms are often seen as operating in “winner-takes-all” markets, implying that they compete *for* the market. However, we do not observe these markets becoming completely monopolized.

1.4.2 Factors mitigating concentration

The existence of multiple digital markets that are oligopolies (e.g., music streaming, live streaming, social networks, etc.) suggests that there is also competition *in* the market. I will briefly outline some factors that mitigate the tendency for the market to tip toward a single dominant platform.

Differentiation. We have seen that network effects can encourage all users to converge on a single platform. However, other factors, such as user preferences, can influence this

⁸As illustrated by concerns raised over Google’s Privacy Sandbox. Google considered removing third-party cookies, which threatened other digital platforms that rely on advertising and user data exploitation.

⁹Lambrecht and Tucker (2015) develop the idea that data does not constitute a competitive advantage in itself. They argue that firms need to focus on improving their exploitation of data to provide value to users rather than amassing important of data.

decision. Platforms have the ability to differentiate themselves and coexist because users may have heterogeneous preferences. For instance, there are empirical evidence of the existence of platform users' taste for privacy (Cecere, Le Guel and Soulié, 2015), but they may be heterogeneous with this respect (Allouard, 2023). Casadesus-Masanell and Hervás-Drane (2015) study how platforms can compete in how much privacy they offer to their users, and show that they can ultimately choose different policies, enabling them to vertically differentiate. Platforms can also adopt different business models to attract users with varying willingness-to-pay (Casadesus-Masanell and Llanes, 2015). Calvano and Polo (2020) show that this kind of differentiation can also arise in the absence of consumer heterogeneity. The possibility for platforms to differentiate in multiple dimension allows for the coexistence of multiple platforms, thereby limiting market concentration (Armstrong, 2006).

Multi-homing. Users can choose to join multiple platforms simultaneously, a practice known as multi-homing. For example, ride-sharing consumers may have several apps installed on their devices, such as Uber, Bolt, and Lyft. This allows them to benefit from different platforms offering very similar services and ultimately choose the one that provides the best fare at any given moment. Similarly, drivers may also multi-home to expand their pool of potential passengers. Naturally, platform users might also multi-home when two or more platforms offer differentiated services or products, such as using both Instagram and Twitter simultaneously for different types of social media interactions. The propensity for users to multi-home naturally limits market concentration and influences the price structure and platform decisions (Armstrong, 2006; Bakos and Halaburda, 2020; Jeitschko and Tremblay, 2020).

Congestion. Another factor that can limit concentration in platform markets is congestion. While I previously discussed the economies of scale inherent in digital markets, there can also be situations where platforms experience decreasing returns to scale due to congestion. Even though digital platforms facilitate interactions and transactions through virtual interfaces, they are still constrained by physical infrastructure like servers.¹⁰ These capacity constraints lead to some form of congestion. Additionally, congestion can also stem from within-group negative externalities such as competition (Belleflamme and Toulemonde, 2009; Karle, Peitz and Reisinger, 2020). These congestion effects can counterbalance the benefits of increasing returns to scale and the attraction loops associated with network effects, resulting in platforms operating in less concentrated markets.

Digital platforms operate in markets with inherent features that naturally lead to

¹⁰For example, during major events like product launches, websites may crash, prompting users to postpone or cancel their visit.

concentration. Despite some mitigating factors, we do observe significant levels of concentration in several digital markets, raising concerns about market contestability and the potential for excessive market power. Given these market characteristics, it is not immediately clear that such concentration is harmful, as large platforms may enhance the benefits of network effects. However, recent competition cases¹¹ have uncovered anti-competitive practices by these large digital conglomerates, which mitigate the potential positive aspects of concentration.

2 Platforms market power and (mis)behavior

The dominant position of some digital platforms, coupled with their vertical and horizontal expansion, has enabled them to engage in various anti-competitive behaviors. This has further reduced market contestability and weakened competition, to the detriment of both end users and other businesses. However, regulators, competition authorities, and policymakers have begun to respond, imposing fines and introducing new regulations aimed at limiting the market power of these dominant firms.

2.1 Lack of market contestability

We have observed that the markets in which platforms operate may naturally exhibit high barriers to entry. However, incumbent platforms can also adopt strategies to artificially raise these barriers. For example, network effects often give incumbents a competitive advantage due to their large, established user base, which consumers prefer (Biglaiser, Calvano and Crémer, 2019). While large platforms could enhance their interoperability with smaller competitors, they frequently choose not to (Crémer, Rey and Tirole, 2000; Doganoglu and Wright, 2006). Additionally, while the ability to multi-home can facilitate the entry of new players in a platform market, platforms may employ strategies like exclusivity contracts and price parity clauses that can hinder the pro-competitive effects of multi-homing. However, Johansen and Vergé (2017) show that these practices should not necessarily be deemed anti-competitive.¹² Yet, it appears that platforms may strategically accentuate or attenuate certain market characteristics to prevent the emergence of competition.

¹¹See, for instance, the European Commission antitrust case AT.39740 on Google Shopping, for which Google was fined on June 27, 2017; the French Competition Authority decision no. 21-D-11 on Google AdX, dated January 7, 2021; and the European Commission antitrust case AT.40437 on Apple's practices in the App Store, for which Apple was fined on March 4, 2024.

¹²Price parity clauses have been a subject of debate in Europe and globally, particularly in the context of online travel agencies like Booking.com. See Hunold, Kesler and Laitenberger (2020*a*) and Mantovani, Piga and Reggiani (2021).

2.2 Hybrid platforms

Many platforms can be considered hybrid platforms, meaning they both provide services to third parties and compete with them simultaneously. Traditionally, such situations have raised concerns about potential foreclosure of competitors (Hart and Tirole, 1990; Ordober, Saloner and Salop, 1990*a*), and these concerns remain relevant in digital contexts. Moreover, these platforms have a large array of tools at their disposal to partially or fully foreclose their competitors. Self-preferencing strategies, where platforms unfairly exploit and leverage their upstream position, are a significant concern. Anderson and Bedre-Defolie (2021) show that a platform operating in an hybrid mode can have incentives to favor its own products.¹³ Hunold, Laitenberger and Thébaudin (2022) provide empirical evidence that Amazon might engage in similar practices on its marketplace. Hagiu, Teh and Wright (2022*a*) discuss the implications of banning such conduct, emphasizing that another crucial aspect of platforms' vertical nature is their ability to leverage a data advantage. A hybrid platform can collect exclusive data and use it unfairly, which can harm competition and hinder innovation (Madsen and Vellodi, 2023). Overall, the hybrid nature of some digital platforms has raised concerns about potentially incentivizing them to engage in anti-competitive conduct.

2.3 Innovation by platforms

Major platforms have emerged and succeeded by being particularly innovative in their technology, design, business models, and more. However, the current market structures in the digital economy can have conflicting effects on innovation. In the context of platforms, D'Annunzio (2017) show that vertically integrated firms may have reduced incentives to innovate in content quality, suggesting that vertical integration, which is prevalent among large platforms, could lead to less innovation. However, the diversity in business models within the digital economy might allow firms to better monetize their innovations, potentially making them more innovative (Etro, 2021*a*).

Additionally, the dynamics at play regarding start-up acquisitions may also affect innovation. Digital technologies have also enabled young start-ups to bring significant societal benefits through their innovative ideas. The GAFAMs recognize that they are not the only entities capable of driving such progress, as evidenced by their numerous acquisitions of young firms. However, this acquisition strategy could alter start-ups' decisions, leading them to anticipate being bought out (Dijk, Moraga-González and Motchenkova, 2024). Entry-for-buyout dynamics may be particularly strong in digital markets, where Big Tech firms dangle the possibility of acquisition, potentially turning it into an objective for start-ups (Eisfeld, 2023). While this could positively impact innovation, concerns remain about the motives behind Big Tech's acquisition patterns. These companies might

¹³See also Etro (2021*b*) and Zenny (2022).

acquire nascent competitors to limit future competition or, in a worse scenario, engage in “killer acquisitions”, depriving consumers of start-ups’ innovative products or technologies.¹⁴ However, there is mitigated evidence of Big Tech carrying out killer acquisitions (Gautier and Lamesch, 2021; Barys and Gautier, 2024).

2.4 Regulating digital platforms

Policymakers around the world have recognized the need for new, appropriate regulations specific to the digital economy. One of the most notable examples is the Digital Markets Act (DMA) in the European Union. Targeting so-called “gatekeepers,” this asymmetric regulation aims to address well-known anti-competitive practices by banning them. The DMA prohibits self-preferencing and steering by gatekeepers, mandates the interoperability of dominant messaging services, and forbids hybrid platforms from leveraging their data advantage, among other provisions. While the DMA restricts the range of actions available to dominant platforms, it remains essential to assess the reluctance of regulated firms to comply, as some have already shown resistance.¹⁵ Authorities must ensure that the law is properly enforced, and it is crucial to conduct policy evaluations (Waldfogel, 2024; Pape and Rossi, 2024). Lastly, it is important that experts continue producing knowledge to help design future regulations, if deemed necessary.

3 Thesis Contributions

This doctoral thesis seeks to identify and understand the strategies of digital platforms and their impact on market outcomes. Drawing on theoretical and empirical industrial organization, I aim to provide insights that will help policymakers and consumers make better decisions in digital contexts.

In the first chapter, co-authored with Marie-Laure Allain and Marc Bourreau, we study platforms’ business model decisions and their impact on incentives to invest in quality-enhancing innovation. We develop a theoretical model with endogenous multi-homing and overlapping viewership, showing that these business model decisions can be a source of distortion that should be considered by regulators. In the second chapter, I develop a theoretical model to examine the ability of an *adtech* stack incumbent to leverage a downstream position in the display advertising market. I show that this can effectively reduce *adtech* contestability and discuss the efficiency of restrictions on online advertising levels. In the final chapter, co-authored with Louis Pape, we conduct an empirical analysis of the online auction platform Catawiki. Our study highlights the

¹⁴See Cunningham, Ederer and Ma (2021) for an analysis of such behavior in the pharmaceutical industry.

¹⁵See non-compliance investigations against gatekeepers: [https://digital-markets-act.ec.europa.eu\[...\]](https://digital-markets-act.ec.europa.eu[...])

importance of platform-curated information provision in auction contexts. We show that Catawiki enhances consumers' valuations of listed objects through value estimations.

3.1 Digital platforms' business model decision and incentives to innovate

Digital platforms actively manage network effects and establish governance rules, including price structures, which dictate their monetization strategies and business models (Rochet and Tirole, 2003). In the digital economy, a wide variety of business models coexist, sometimes within the same market (e.g., retail cloud services). Calvano and Polo (2020) demonstrate that business model differentiation can arise not necessarily due to user heterogeneity, but because of strategic substitutability between business models. Etro (2021a) discusses how, in situations where different business models coexist, monetization strategies can significantly impact innovation incentives, leading some firms to be more innovative than others. In this chapter, we examine how platforms' choice of business model can affect their incentives to invest in quality-improving innovation, and how these investments, in turn, influence their business model decisions.

We consider a platform duopoly, where firms can decide to be *ad-funded* or *device-funded* (charging an access fee to consumers). Moreover, platforms can invest in quality-enhancing innovation for their consumers. Their incentives to do so depend on their ability to monetize their innovation. We find that business model differentiation can arise despite platforms being *ex-ante* identical, as it can allow platforms to charge monopoly prices in the advertising market. By comparing the equilibrium with the consumer surplus maximizing configuration, we identify a new source of distortion realized through business model decision. We emphasize that policy makers should take into account how they influence business model decisions as it might result in platforms users harm.

This study has interesting policy implications. For instance, we argue that competition policy, or any policy that could influence the profitability of one business model over another, might seem like a good idea *a priori*. Indeed, enhancing platforms' ability to monetize their innovations can be beneficial to consumers. However, policymakers need to consider the impact of such a policy on platforms' business model decisions, as it could lead to a change in equilibrium and potentially harm consumers.

3.2 Integration in online display advertising, *adtech* contestability, and advertising restrictions

Vertical integration in concentrated digital markets has been a primary concern for academics and practitioners in recent years (de Cornière and Taylor, 2014; Hagiü, Teh and Wright, 2022a). Moreover, the online advertising market has particularly sparked con-

cerns due to the presence of extremely dominant players. The Competition and Markets Authority (2020) issued a report focusing on various online advertising industries, notably highlighting Google’s dominance in the *adtech* stack, which is the chain of technological intermediaries that matches advertisers with ad publishers. Regarding actual cases, the French Competition Authority has imposed a fine of 220 million euros on Google for anti-competitive practices in the *adtech* stack.¹⁶ According to both the British and the French competition authorities, Google’s dominance in the display advertising technology provision market is established, and the contestability of this market is rather low. In this chapter, we study the impact of Google’s downstream position with YouTube on the contestability of the *adtech* stack and the competition for consumer attention. Despite being briefly discussed by the Competition and Markets Authority (2020), this aspect of the state of the online display advertising market has been overlooked.

Our findings suggest that the integration of an *adtech* stack incumbent (e.g., Google) with a downstream display advertising platform (e.g., YouTube) can effectively and artificially raise barriers to entry. This is achieved in two ways. First, the acquisition of the display advertising platform can prevent any new entrant from competing for the newly acquired ad space, reducing entry profitability. Second, there is a collusive effect of integration that pushes the independent publisher to “make a deal with the devil” (Chen, 2001). An *adtech* stack incumbent can effectively use integration to leverage its downstream position, reducing market contestability as well as the level of competition for consumer attention. Ultimately, consumers are exposed to more ads, and integration is unilaterally detrimental to them.

We extend our analysis by considering that a regulator might want to impose advertising restrictions, similar to the European Union’s legislation on commercial breaks on TV.¹⁷ Such a restriction could prove useful in protecting consumers from excessive exposure to ads resulting from integration and could potentially improve market contestability. More precisely, a lenient restriction would lightly limit consumers’ excessive exposure to ads while improving market contestability. However, if the restriction is strict and sets an advertising level cap below the competitive level, it would effectively protect consumers but ultimately reduce *adtech* contestability.

This study provides interesting policy insights as we examine a novel aspect of the concentration and vertical integration in the online display advertising industry. Adding to the concerns raised by Google’s position in the *adtech* stack, we argue that it may be able to leverage its downstream position and raise barriers to entry. However, restricting advertising levels might be a credible and efficient tool to limit these harmful effects of integration.

¹⁶See decision no. 21-D-11 available at: <https://www.autoritedelaconurrence.fr/fr/communiqués-de-presse/lautorite-de-la-concurrence-sanctionne-google-hauteur-de-220-millions-deuros>

¹⁷In the EU, commercial breaks on television cannot account for more than 20% of hourly airtime.

3.3 Product value information provision by online auction platforms

Reducing the cost of information acquisition for agents is a major way through which platforms can create value and develop a sustainable business model. In auction contexts, the theoretical literature extensively emphasizes the critical importance of information provision and acquisition (Milgrom, 1981). Empirical works highlight the impact of different kinds of information provision by auction platforms on consumers' willingness to pay (Livingston, 2005; Jin and Kato, 2006). The design of the system that generates the information is also very important (Cai et al., 2014). However, the platforms' incentives may be misaligned with the interests of platform users, and the information provided could be biased. In our case, we study platform-curated value estimations. On the online auction platform Catawiki, potential bidders can be provided with an estimation window for a specific product given by an in-house expert. We focus on assessing how this information provision from the platform can impact seller and buyer behaviors.

On Catawiki, listed objects can receive value estimates from experts employed by the platform. These estimates consist of a minimum and a maximum value. They could provide useful information to potential bidders to help them assess their willingness to pay, but they might also distort this assessment in the interest of the platform. We leverage variations in the value of the maximum estimate relative to the minimum estimate and find sizable and statistically significant effects on seller and buyer behavior. Moreover, to account for potential omitted variable bias, we exploit quasi-random variations in the experts' daily propensity to provide high estimates in the form of instrumental variables.

We show that, despite being systematically overinflated, estimates benefit from user trust. Holding the value constant, a high ratio of the maximum to minimum estimate increases the final prices, generating larger platform revenues. Sellers also adjust their behavior by surprisingly decreasing their propensity to set a reserve price. As a result, they benefit from higher prominence on the platform and greater entry from bidders. Accounting for these effects, we still find sizable and significant effects of estimates on the final price, suggesting an impact on buyers' valuation of the goods. We identify an upper limit to this behavior, which is rarely reached in practice, indicating that the platform arguably makes a reasonable use of this demand-shifting tool.

This study provides valuable managerial and policy insights. It highlights the critical role of platform-provided information in enhancing market efficiency. In an auction context, reducing the cost of information acquisition for buyers leads to increased bidder participation, higher prices, and greater revenues. If an auction platform is listing a reasonable number of items, it may consider providing value estimates to help buyers better assess their willingness to pay. However, a social planner might have legitimate concerns about potential biases in the value information provided by the platform, as it seeks to

maximize its profits.

Chapter 1

Digital Business Models and Quality Investment

1 Introduction

The last two decades have witnessed the emergence of a vibrant platform economy, bringing significant benefits to society and the economy due to sharp cost reductions (Goldfarb and Tucker, 2019) and innovation in products and services (Aguiar and Waldfogel, 2018). Incremental innovation by digital platforms to reduce service costs or improve quality is also occurring rapidly, particularly through the extensive use of user data and artificial intelligence algorithms. Still, the dominance of a few large platforms has raised competition and regulatory concerns about whether competition is working properly in these markets.

Digital platforms have adopted a variety of business models. Some platforms generate revenue by selling products or charging subscriptions for access to their digital services. Others offer their products or services for free to consumers and generate revenue by charging other sides of their market, typically advertisers. The choice of business model can affect competition in platform markets in several ways. In this paper we examine how platforms' choice of business model can affect their incentives to invest in quality-improving innovation, and how these investments, in turn, influence their business model decisions.

We study the competition between two horizontally differentiated platforms offering services (e.g., content) to consumers. Platforms can choose to be either *device-funded* or *ad-funded*. A device-funded platform is funded solely by the sale of a device or by charging membership fees to users. Examples of such platforms include Apple (which relies mainly on the sale of devices such as the iPhone) and Netflix (which relies primarily on subscription fees). Platforms can also choose to be (purely) ad-funded, that is, supported only by the sale of advertising space to advertisers. In this case, users access the platform

for free, but ads can be a nuisance to them. Examples of ad-funded platforms include YouTube and Facebook.

A device-funded platform sets the price of its device, while an ad-funded platform does not charge consumers for access to its services, but sets a price to advertisers for ad space. Platforms can also invest to improve the quality of their services. Consumers are heterogeneous in their preferences for the two platforms and decide which platform(s) to join. They can single-home (join only one platform) or multi-home (join both platforms), and we focus on equilibria with partial multi-homing. Consumers dislike ads, which represent a nuisance to them. As Anderson, Foros and Kind (2018), we assume that consumers do not observe the ad levels on the platforms before making their homing decision, but form rational expectations about these levels.

We begin by analyzing the platforms' pricing and investment decisions, taking their business models as given. We consider the three possible business model configurations that can arise: both platforms are device-funded, both are ad-funded, or one is device-funded while the other is ad-funded. We compare the equilibrium quality investments, profits, and consumer surplus in these different configurations.

We find that quality investment is higher for a device-funded platform than for an ad-funded platform when the value of the service to consumers is higher than the value of exposing a marginal consumer to ads to advertisers (and vice versa). Which business model configuration yields the highest profit for platforms depends on the *return to ads* (Jullien and Bouvard, 2023), that is, the ratio between the value of a marginal eyeball to advertisers and the nuisance of ads. If the return to ads is less than 1 (the "return" of a standard device or membership fee), platforms are better off if they are both device-funded. It takes a return on ads much higher than 1 for platforms to make higher profits when they are ad-funded. This reflects that with an ad-funded business model, platforms can only influence user demand through quality investments, as users have passive beliefs about the level of advertising. Interestingly, in this case, each ad-funded platform would be better off if its rival were device-funded. This is because competition in the advertising market is fierce when they are both ad-funded, which erodes their profits.

When the return to ads is less than 1, consumers are also better off when both platforms are device-funded. When the return to ads is greater than 1, consumers are better off when at least one platform is ad-funded. When the value of multi-homer in the advertising market is highly discounted due to competition between platforms for advertisers, consumers prefer differentiated business models because it leads to higher quality investments.

In a second step, we endogenize the business model decision of the platforms. When the return to ads is low, in equilibrium, both platforms choose to be device-funded, as monetizing the service through users becomes more feasible than through advertisers. This configuration maximizes consumer surplus when the ad return is less than 1. How-

ever, as the return to ads increases, both platforms still tend to adopt a symmetric, device-funded model, though consumers would prefer at least one platform to switch to an ad-funded model. When the return to ads is larger, at least one platform is ad-funded in equilibrium. Whether the platforms decisions are aligned with consumers interests then also depends on the discount for a second impression, which impacts platforms decisions through the price on the advertising market.

Our paper is closely related to the strand of literature that investigates the business model decision of multi-sided platforms. Casadesus-Masanell and Zhu (2010) study the best response of an incumbent platform facing a new *ad-funded* competitor. They analyze reactions in terms of prices or number of ads, but also consider the possibility for the incumbent to change its business model. They show that it is optimal for the incumbent to adopt a pure *device-funded* or *ad-funded* business model rather than a mixed business model. Casadesus-Masanell and Llanes (2015) study the competition between two platforms that can derive revenue from subscriptions and by selling consumer data in a secondary market, which consumers dislike. They show that the platforms have an incentive to focus on a single revenue stream and to differentiate their business models. Calvano and Polo (2020) study the competition between two media platforms that can generate revenue from subscriptions and advertising in a setting with homogeneous users and advertisers. They show that even if the agents are not heterogeneous, the platforms can be differentiated in equilibrium. This is because the device-funded and ad-funded business models are strategic substitutes: if one media platform chooses to be more “device-funded” (i.e., to raise subscription fees and lower ad levels), the rival has an incentive to be more “ad-funded” (i.e., to raise ad levels).¹

Our paper is also related to the strand of literature that investigates how firms’ innovation incentives are influenced by their business model.² Etro (2021*a*) analyzes the competition between two platforms based on a device. Each platform sells a device with an app store that hosts services from independent app developers. One platform is “device-funded” (i.e., derives most of its revenue from the sale of the device), while the other is “ad-funded” (i.e., derives revenue from advertising). He then analyzes the impact of the platforms’ business models on their incentives to invest in app curation and the development of new in-house apps. Casadesus-Masanell and Llanes (2015) study incentives to invest in quality by a monopoly software or hardware platform, considering two possible business models, proprietary and open source. A proprietary platform decides on its investment in platform quality, while for an open source platform the in-

¹See also Weeds (2013).

²Other relevant but less related literature has examined the impact of the acquisition of startups by dominant platforms (see, e.g., Rasmusen (1988), Cunningham, Ederer and Ma (2021), Dijk, Moraga-González and Motchenkova (2021)) and the impact of mergers on innovation (see, e.g., Mermelstein et al. (2020), Federico, Langus and Valletti (2017), Denicolò and Polo (2018), Bourreau, Jullien and Lefouili (2024)).

vestment is made by the independent complementors. In particular, the authors show that investment in platform quality can be higher in the open source model if an open source platform attracts more users.

Our main contribution to the literature is to endogenize both the quality investment decision of platforms (as in the first strand of the literature) and their business model decision (as in the second strand of the literature). We study how platforms' business models shape their incentives to invest in quality, but also their endogenous choice of business models.

The rest of the paper is organized as follows: In Section 2, we introduce the model. In Section 3, we take the platforms' business models as given and analyze their pricing and quality investment decisions in each possible business model configuration. In Section 4, we endogenize the business model decisions of the platforms. Finally, in Section 5 we discuss the policy of our results, and in Section 6 we conclude.

2 The model

We consider two platforms, 1 and 2, which offer services (e.g., content) to users at a constant marginal cost normalized to zero. The platforms are horizontally differentiated on an *Hotelling* line of length 1, with platform 1 located at $x_1 = 0$ and platform 2 at $x_2 = 1$. A mass 1 of users is uniformly distributed along the line. A user located at x incurs the transportation cost $|x - x_i|$ if she consumes the content of platform $i = 1, 2$. Users can single-home (join only one platform) or multi-home (join both platforms). A multi-homer receives the sum of the utilities of joining both platforms (i.e., there is no overlap of content between the two platforms).

The two platforms are also vertically differentiated. When consuming platform i 's service, a consumer receives the utility $v + q_i$, where $v > 0$ is an intrinsic utility and q_i is the quality of service of the platform. To provide a quality of service q_i , platform i must incur the investment cost $c(q_i) = q_i^2/2$.

A platform $i \in \{1, 2\}$ can be either *device-funded* or *ad-funded*.³ If it is device-funded, the platform charges users a device or membership fee $f_i \geq 0$ but does not display ads. For a user located at x , the net utility from joining platform i is then $u_i = v + q_i - f_i - |x - x_i|$.

If it is ad-funded, the platform provides access to users free of charge. In return, it displays ads and charges advertisers a price p_i for an ad campaign. An ad campaign exposes all users of the platform to the ad. There is a unit mass of homogeneous advertisers. Showing an ad once to a user brings value $\sigma > 0$ to the advertiser. Showing an ad twice to the same user has value $\sigma + \beta\sigma$, where $\beta \in [0, 1]$. Therefore, the second impression is discounted by β , as it is less effective if the user has already been informed by the first

³As Etro (2021a), we take the ad-funded and device-funded business models as given. See, e.g., Casadesus-Masanell and Llanes (2015) for a model where business models emerge endogenously.

ad.⁴ However, users dislike ads. If users expect a level of advertising r_i^e on platform i , they face the disutility γr_i^e , with $\gamma \geq 0$. For a user located at x , the net utility from joining platform i is then $u_i = v + q_i - \gamma r_i^e - |x - x_i|$.

Timing. The timing is as follows:

- In Stage 1, platforms simultaneously choose their business model (device-funded or ad-funded). These choices are observable to all.
- In Stage 2, platforms choose their investment in quality q_i .
- In Stage 3, platforms observe each other's investment. The device-funded platforms set their device or membership fee f_i . The ad-funded platforms set their ad-campaign price p_i . Advertisers observe the prices and decide on which platform(s) to run an ad campaign.
- In Stage 4, users observe the business models of the platforms and the device fees, if any. They do not observe the advertising level on platforms, but as in Anderson, Foros and Kind (2018), they form rational expectations about advertisers' participation on each platform. Then, users decide which platform(s) to join.

We look for the subgame perfect Nash equilibria (SPNE) of this game.

Depending on platforms' business model decisions, either both platforms are device-funded, both are ad-funded, or one is ad-funded while the other is device-funded. In the rest of the paper, we denote by X_{b_i, b_j} the equilibrium value of X for firm i at Stage 2 of the game (where X can represent prices, quality investments, profits, etc.) when firm i has adopted the business model b_i and the rival firm $j \neq i$ has adopted the business model b_j , with $b_i, b_j \in \{A, D\}$.

Assumption 1 guarantees that for each business model configuration, in equilibrium the market is covered and there is *partial* multi-homing (i.e., some - but not all - users multi-home).

Assumption 1 (*Market coverage and partial multi-homing*)

$$(a) \quad 1/2 < v \leq 1$$

$$(b) \quad \sigma_{min} \equiv \frac{1}{\beta} \cdot \left(\frac{1}{2} + \gamma - v\right) \leq \sigma \leq \sigma_{max} \equiv 1 + \gamma - v$$

Assumption 1 (a) implies that in the symmetric device-funded vs. device-funded configuration, the market is covered and there is partial multi-homing. Assumption 1 (b) implies, combined with the previous one, that we have partial multi-homing in the device-funded vs. ad-funded and ad-funded vs. ad-funded configurations.⁵

⁴These assumptions are standard in the advertising literature when there is overlapping viewership. See, e.g., Ambrus and Reisinger (2006) and Anderson and Jullien (2015).

⁵For more details, see Appendix 7.1.

3 Pricing and investment decisions

In this section, we take the platforms' business models as given. For each business model configuration, we examine the platforms' pricing and investment decisions, as well as the participation decisions of users and advertisers.

3.1 Device-funded vs. device-funded

First, suppose that both platforms are device-funded – we denote this configuration as DD . Since no platform offers ad space, advertisers stay out of the market. As usual, we solve the game backwards.

Users' homing decision. In the last stage, users can single-home or multi-home. So, a user joins a given platform if she makes a positive net utility. Therefore, a user located at x joins platform 1 if

$$x \leq v + q_1 - f_1 \equiv \hat{x}_1,$$

and joins platform 2 if

$$x \geq 1 - (v + q_2 - f_2) \equiv \hat{x}_2.$$

The user multi-homes if both conditions are satisfied, which is the case if $\hat{x}_2 \leq x \leq \hat{x}_1$. Hence, the demand for platform 1 is \hat{x}_1 , the demand for platform 2 is $1 - \hat{x}_2$, and there are $\hat{x}_1 - \hat{x}_2$ multi-homers.

It is interesting to note that platform $i = 1, 2$ cannot influence the size of its single-homing segment, \hat{x}_j . Indeed, \hat{x}_j depends only on the other platform j 's decisions (f_j and q_j). However, platform i 's decision affects the size of its multi-homing segment ($\hat{x}_1 - \hat{x}_2$), and ultimately the size of its total demand (\hat{x}_i).

Fees. In stage 3, platforms anticipate users' decisions and set their fees, taking as given their quality investment in the previous stage. Platform i 's profit is given by:

$$\Pi_i(q_i, f_i) = f_i \cdot (v + q_i - f_i) - c(q_i). \quad (1.1)$$

This profit function is concave in f_i , and the first-order condition yields an optimal fee of:

$$f_i(q_i) = \frac{v + q_i}{2}. \quad (1.2)$$

Since we have assumed that the utility a multi-homer derives from one platform is independent of the utility she derives from the other platform, there is no strategic interaction between the platforms. As a result, they each behave as a monopolist on their side of the market, even though they share some users through multi-homing.

Quality investment. In stage 2, platforms choose their level of quality investment, anticipating the effect of their investment on user demand and their ability to charge higher fees. Platform i 's profit is given by:

$$\Pi_i(q_i, f_i(q_i)) = f_i(q_i)(v + q_i - f_i(q_i)) - c(q_i) = \frac{(v + q_i)^2}{4} - \frac{q_i^2}{2}. \quad (1.3)$$

The first-order condition is

$$\frac{\partial \Pi_i}{\partial q_i} = f_i(q_i) - c'(q_i) = \frac{v + q_i}{2} - q_i = 0,$$

which gives the platform's optimal level of investment $q_i = v$.

When choosing its level of investment, the platform considers the effect of a quality increase on the marginal consumer. The marginal user is a multi-homer, but the device-funded platform values single and multi-homers equally as it does not price discriminate between them.

Lemma 1 *When the two platforms are device-funded, in equilibrium, the platforms invest $q_{DD} = v$ in quality and charge the fee $f_{DD} = v$. Platforms' profits are $\Pi_{DD} = \frac{v^2}{2}$.*

One can easily verify that under Assumption 1, there is partial multi-homing in equilibrium. Also, notice that the equilibrium profit Π_{DD} is positive, meaning that in this symmetric configuration, it is always sustainable to be device-funded.

Finally, in equilibrium consumer surplus -defined as the sum of all of users' net utility- is as follows:

$$CS_{DD} = \underbrace{\int_0^v (v - x) dx}_{\text{CS from platform 1}} + \underbrace{\int_{1-v}^1 [v - (1 - x)] dx}_{\text{CS from platform 2}} = v^2.$$

In this configuration, consumer surplus depends only on the baseline utility that consumers receive from joining a platform, because the platforms are able to extract all of the additional user surplus generated by their investment ($f_{DD} = q_{DD}$ in equilibrium).

3.2 Device-funded vs. ad-funded

Now, consider the asymmetric configuration in which one platform is device-funded, whereas the other is ad-funded. Without loss of generality, we assume that platform 1 is device-funded and platform 2 is ad-funded. We denote this configuration as DA .

Users' homing decision. Users observe the fee f_1 charged by platform 1 and make expectations about the level of advertising on platform 2, r_2^e . Then, a user located at x

joins platform 1 if

$$x \leq v + q_1 - f_1 \equiv \hat{x}_1,$$

and joins platform 2 if

$$x \geq 1 - (v + q_2 - \gamma \cdot r_2^e) \equiv \hat{x}_2.$$

The user multi-homes if $\hat{x}_2 \leq x \leq \hat{x}_1$.

As above, platforms can only influence the size of their total demand but not the composition of demand. It is the other platform's decisions that influence the size of the single-homing segment.

Advertising price and advertisers' participation decision. In this configuration, only platform 2 offers advertisers the possibility to run an ad campaign. Therefore, each impression is unique and valued at σ by advertisers, regardless of whether users single-home or multi-home. So, advertisers decide to run an ad campaign on platform 2 if

$$\sigma(1 - \hat{x}_2) - p_2 \geq 0. \tag{1.4}$$

Lemma 2 *There exists a unique equilibrium where the ad-funded platform sets the advertising price*

$$p_2 = \sigma(v + q_2 - \gamma),$$

each advertiser runs an ad-campaign on platform 2, and users rationally expect $r_2^e = 1$.

Proof. Platform 2 can raise its ad price until the advertisers' participation constraint (1.4) binds, so $p_2 = \sigma(1 - \hat{x}_2)$. At this price, all advertisers place an ad on the platform, leading to an ad intensity of 1, which users rationally expect, so $r_2^e = 1$, giving the result. ■

The ad-funded platform holds a viewership monopoly over its users, whether they single-home or multi-home, enabling it to capture all of the advertisers' surplus. It can set its ad price at the advertisers' valuation and still induce them to run an ad campaign. As users do not observe advertisers' participation before deciding which platform(s) to join, an *ex-post* increase or decrease in the ad level will not affect user demand. Hence, the ad-funded platform charges the maximum ad price consistent with advertiser participation. Users anticipate this and form their expectations about the level of advertising accordingly.

Fee. Because it monetizes all users in the same way (i.e., it does not price discriminate between single-homers and multi-homers), the device-funded platform is unaffected by the other platform's business model. Its pricing decision is affected by the total demand, but not by the composition of demand, while the rival platform's decisions affect the composition of demand, but not the total demand. As a result, the optimal fee is the

same as in the DD configuration:

$$f_1 = \frac{v + q_1}{2}.$$

Quality investment. In stage 2, platforms decide how much to invest in quality. First, consider the device-funded platform. As explained above, its decision is unaffected by the other platform's business model, hence its optimal investment is the same as in the DD configuration. We thus have

$$\begin{aligned} q_1 = q_{DD} = v &\equiv q_{DA}, \quad f_1 = f_{DD} = v \equiv f_{DA} \\ &\text{and} \\ \Pi_1 = \Pi_{DD} = \frac{v^2}{2} &\equiv \Pi_{DA}. \end{aligned}$$

Consider now the ad-funded platform. It maximizes its (concave) profit, $p_2 - c(q_2) = \sigma(v + q_2 - \gamma) - \frac{q_2^2}{2}$, with respect to the investment level q_2 . The first-order condition yields

$$q_2 = \sigma. \tag{1.5}$$

The ability of an ad-funded platform to set a high price for ad space depends on user participation. What matters is the value of the marginal user to advertisers, who is a multi-homer. As there is no overlapping viewership, it is the same as a single-homer and is equal to σ . We thus obtain the following result:

Lemma 3 *When one platform is device-funded and the other is ad-funded, in equilibrium, the device-funded platform's investment, fee and profit are $q_{DA} = v = q_{DD}$, $f_{DA} = v = f_{DD}$, and $\Pi_{DA} = \frac{v^2}{2} = \Pi_{DD}$, whereas the ad-funded platform's investment, price for ad space and profit are $q_{AD} = \sigma$, $p_{AD} = \sigma \cdot (v + \sigma - \gamma)$, and $\Pi_{AD} = \sigma \cdot (v + \sigma - \gamma) - \frac{\sigma^2}{2}$.*

Assumption 1 guarantees that we have partial multi-homing in equilibrium. It is also interesting to note that a device-funded platform makes the same positive profit when it faces a device-funded or an ad-funded platform. It follows that:

Remark 1 *A device-funded platform is profitable, regardless of the business model of the competing platform.*

For this reason, we do not need to make assumptions about the profitability of each business model in each configuration. When we examine the business model decisions, platforms will always have the possibility to make positive profits by being device-funded.

As in the DD configuration, the device-funded platform extracts all of the additional surplus generated by its investment. The ad-funded platform, however, does not charge

the users directly. It generates an additional surplus σ from its investment from advertisers and “charges” users with an ad nuisance of γ . Consumer surplus is then as follows:

$$CS_{DA} = \underbrace{\int_0^v (v-x) dx}_{\text{CS from D}} + \underbrace{\int_{1-(v+\sigma-\gamma)}^1 [(v+\sigma-\gamma) - (1-x)] dx}_{\text{CS from A}} = \frac{v^2}{2} + \frac{(v+\sigma-\gamma)^2}{2}.$$

As in the device-funded vs. device-funded configuration, consumer surplus increases with the baseline utility v . Furthermore, in the relevant parameter space, it increases in the value of an impression σ , and decreases in the ad-nuisance parameter γ .

3.3 Ad-funded vs. ad-funded

Finally, we consider the symmetric configuration AA in which both platforms are ad-funded. The platforms are free to users, but they offer ad space to advertisers, exposing users to nuisance from advertising.

Users’ homing decision. Users know that both platforms display ads, but they do not observe the level of advertising before deciding which platform(s) to join. So, they base their homing decision on their expectations r_i^e about the level of advertising on platform $i \in \{1, 2\}$. Then, a user located at x joins platform 1 if

$$x \leq v + q_1 - \gamma \cdot r_1^e \equiv \hat{x}_1,$$

and joins platform 2 if

$$x \geq 1 - (v + q_2 - \gamma \cdot r_2^e) \equiv \hat{x}_2.$$

The user multi-homes if $\hat{x}_2 \leq x \leq \hat{x}_1$.

Let us define SH_i as the number of users single-homing on platform i and MH as the number of multi-homers. We have $SH_1(q_2, r_2^e) = \hat{x}_2$, $SH_2(q_1, r_1^e) = 1 - \hat{x}_1$, and $MH(q_1, q_2, r_1^e, r_2^e) = \hat{x}_1 - \hat{x}_2$.

Advertising price and advertisers’ participation decision. In this configuration, both platforms offer ad space and some users multi-home. If an advertiser runs an ad campaign on both platforms, multi-homing users will be exposed to the ad twice. As the second impression is discounted by $\beta \in [0, 1]$, the value of showing an ad twice to a multi-homer is $\sigma(1 + \beta)$.

Consider an advertiser running an ad campaign on platform $i \in \{1, 2\}$ only. This generates a gross value of $\sigma \cdot SH_i + \sigma \cdot MH$ for the advertiser, as the multi-homers are only reached once. The *incremental value* of running the ad campaign on the other

platform $j \neq i$ as well is then $\sigma \cdot SH_j + \beta \cdot \sigma \cdot MH$. Indeed, doing so allows the advertiser to reach platform j 's single-homers for the first time, and the multi-homers for the second time. This affects the platforms' pricing strategy, as shown by the following Lemma.

Lemma 4 *There exists a unique equilibrium in which each platform sets an ad-campaign price equal to*

$$p_i = \sigma \cdot SH_i + \beta \cdot \sigma \cdot MH \quad (\text{for } i \in \{1, 2\})$$

such that all advertisers participate, users rationally expect $r_i^e = 1$, $SH_i = 1 - (v + q_j - \gamma)$ and $MH = (v + q_i - \gamma) + (v + q_j - \gamma) - 1$.

Proof. The proof follows Anderson, Foros and Kind (2018)'s Proposition 1 and their *incremental pricing principle*. It is an equilibrium as no platform has an incentive to deviate. If a platform increases its price, it loses all advertiser demand. If the platform lowers its price, it will not be able to attract additional advertisers as they are all already running an ad campaign. It is unique because in any other candidate equilibrium, the platforms have a profitable deviation which consists in pricing at this *incremental value* while still getting all advertisers to run an ad campaign. Hence, both platforms price at the *incremental value*, all advertisers advertise on both platforms, and users rationally expect $r_i^e = 1$ for $i \in \{1, 2\}$. ■

In this symmetric configuration, the discount parameter β captures the intensity of competition in the advertising market. As it decreases, the second impression becomes more and more discounted, leading to a lower *incremental value* and ultimately to fiercer advertising price competition. Multi-homers are less valuable to platforms than single-homers, as they do not enjoy a monopoly position on their viewership. Hence, in this symmetric configuration with two ad-funded platforms, the composition of demand matters for firms' profits.

Quality investment. In stage 2, platform i 's profits are given by:

$$\Pi_i^{AA} = p_i - c(q_i) = \sigma \cdot SH_i(q_j) + \beta \cdot \sigma \cdot MH(q_i, q_j) - c(q_i). \quad (\text{for } i \in \{1, 2\})$$

Ad-funded platforms simultaneously choose their investment levels to maximize their profits. The first-order condition yields:

$$\beta \cdot \sigma \cdot \frac{\partial MH}{\partial q_i} = c'(q_i). \quad (\text{for } i \in \{1, 2\})$$

As $\partial MH / \partial q_i = 1$, we obtain $q_i = \beta \cdot \sigma$.

As in the other configurations, platforms consider the value of the marginal user they can attract by increasing their investment in quality. This user is a multi-homer, hence

in equilibrium, platforms' investment is equal to $\beta \cdot \sigma$, which is lower than the investment made by an ad-funded platform in the asymmetric setting DA .

Lemma 5 *When both platforms are ad-funded, in equilibrium, the platforms invest $q_{AA} = \beta \cdot \sigma$ in quality and charge $p_{AA} = \sigma \cdot SH_{AA} + \beta \cdot \sigma \cdot MH_{AA}$ for ad space. Platforms' profits are $\Pi_{AA} = \beta\sigma(v + \beta\sigma - \gamma) + \sigma(1 - \beta)[1 - (v + \beta\sigma - \gamma)] - \frac{(\beta\sigma)^2}{2}$.*

Assumption 1 ensures that there is partial multi-homing in equilibrium.

Finally, in equilibrium consumer surplus is as follows:

$$\begin{aligned}
 CS_{AA} &= \underbrace{\int_0^{v+\beta\cdot\sigma-\gamma} [(v + \beta \cdot \sigma - \gamma) - x] dx}_{\text{CS from platform 1}} + \underbrace{\int_{1-(v+\beta\cdot\sigma-\gamma)}^1 [(v + \beta \cdot \sigma - \gamma) - (1 - x)] dx}_{\text{CS from platform 2}} \\
 &= (v + \beta \cdot \sigma - \gamma)^2.
 \end{aligned}$$

As before, consumer surplus increases with the baseline utility v and the value of an impression σ , and decreases with the ad-nuisance parameter γ .

3.4 Comparison of business model configurations

Finally, we compare quality investments, profits, the value for users, and consumer surplus in the different business model configurations.

Quality investments. As multi-homing does not affect a device-funded platform's ability to extract surplus from users, such a platform behaves as a monopolist, and invests v in quality regardless of the business model chosen by its competitor. By contrast, an ad-funded platform invests more when its rival is device-funded than when it is ad-funded, because the value of an ad that reaches a multi-homer is not discounted.

Proposition 1 *Quality investments in the different business model configurations compare as follows:*

- *If $\sigma < v$, $q_{DD} = q_{DA} > q_{AD} \geq q_{AA}$. Regardless of the rival's business model, a device-funded platform invests in quality more than an ad-funded platform.*
- *If $v \leq \sigma < v/\beta$, $q_{AD} \geq q_{DD} = q_{DA} > q_{AA}$. When facing a device-funded rival, an ad-funded platform invests more than a device-funded platform; by contrast, an ad-funded platform invests less than a device-funded platform when facing an ad-funded rival.*
- *If $\sigma \geq v/\beta$, $q_{AD} \geq q_{AA} \geq q_{DA} = q_{DD}$. Regardless of the rival's business model, an ad-funded platform invests more than a device-funded platform.*

Profits. A device-funded platform is indifferent to the other platform’s business model and always receives the same profit, $v^2/2$, which increases in v . By contrast, ad-funded platforms are affected by the other platform’s business model.

Proposition 2 *Platform profits in the different business model configurations compare as follows:*

- If $\sigma < \hat{\sigma} \equiv \gamma - v + \sqrt{v^2 + (v - \gamma)^2}$, $\Pi_{DD} = \Pi_{DA} > \Pi_{AD} \geq \Pi_{AA}$.
- Otherwise, if $\sigma \geq \hat{\sigma}$, $\Pi_{AD} \geq \Pi_{DA} = \Pi_{DD}$ and $\Pi_{AD} \geq \Pi_{AA}$.

Proof. See Appendix 7.2. ■

To discuss this proposition, it is interesting to introduce the *return to ads* $r \equiv \sigma/\gamma$, as in Jullien and Bouvard (2023). When $r = 1$, the ad-funded business model provides the same return as the device-funded business model. When $r > 1$, it is more efficient, and when $r < 1$ it is less efficient.

Now, notice that the threshold $\hat{\sigma}$ defined in Proposition 2 is higher than γ . Therefore, if the return to ads is less than 1, platforms make higher profits if they are device-funded. However, as $\hat{\sigma}/\gamma > 1$, platforms may still prefer to be device-funded when the return is (slightly) higher than 1. The return to ads must be sufficiently higher than 1 for the platforms to make higher profits with the ad-funded business model. The reason is that users in our setting have passive beliefs about advertising, and therefore platforms can only influence demand through (costly) quality investments.

The proposition also shows that it is always more profitable for an ad-funded platform to be the only platform offering ad space. This is because, when both platforms are ad-funded, the competition in the advertising market is intensified, which drives down the platforms’ profits.

Quality-adjusted prices. As previously discussed, device-funded platforms are unaffected by the other platform’s business model, so users derive the same utility from patronizing a device-funded platform in any configuration.

Furthermore, we have seen that ad-funded platforms expose their users to the same nuisance regardless of their rival’s business model— the ad-nuisance cost will always be γ to the users. However, ad-funded platforms invest more if the rival platform is device-funded.

We can consider the nuisance of advertising as the equivalent of a price to users. We can then compare the quality-adjusted “prices” in the different business model configurations. Let us define $\hat{p}_{b_i b_j}$ as firm i ’s quality-adjusted price when it has adopted the business model b_i and its rival has adopted the business model b_j , with $b_i, b_j \in \{D, A\}$. For a device-funded platform, the quality-adjusted price is always 0, i.e., $\hat{p}_{DD} = \hat{p}_{DA} = 0$.

For an ad-funded platform, the quality-adjusted price is $\hat{p}_{AD} = \gamma - \sigma$ if it competes with a device-funded platform, and $\hat{p}_{AA} = \gamma - \beta\sigma$ if it competes with an ad-funded platform.

We then have the following result:

Proposition 3 *Quality-adjusted prices in the different business model configurations compare as follows:*

- If $\sigma < \gamma$, $\hat{p}_{AA} \geq \hat{p}_{AD} > \hat{p}_{DA} = \hat{p}_{DD}$. The quality-adjusted price for the device-funded platform is always lower.
- If $\gamma \leq \sigma < \gamma/\beta$, $\hat{p}_{AA} > \hat{p}_{DA} = \hat{p}_{DD} \geq \hat{p}_{AD}$. When the rival platform is device-funded, the quality-adjusted price is lower for an ad-funded platform than for a device-funded one; conversely, when the rival platform is ad-funded, the quality-adjusted price is lower for an a device-funded platform than for ad-funded one.
- If $\sigma \geq \gamma/\beta$, $\hat{p}_{DA} = \hat{p}_{DD} > \hat{p}_{AA} \geq \hat{p}_{AD}$. The quality-adjusted price for the ad-funded platform is always lower.

Consumer surplus. Consumer surplus depends on quality-adjusted prices, but also on transportation costs. Therefore, we now compare the consumer surplus in the different configurations.

As we have seen in Section 3, a device-funded platform is able to extract all of its users' surplus from its investment through the fee, leaving them with a surplus corresponding to the intrinsic value v , hence it generates a consumer surplus of $\frac{v^2}{2}$ regardless of the rival's business model. By contrast, the consumer surplus generated by an ad-funded platform depends on its rival's business model: if it faces a device-funded rival, the ad-funded platforms generates a consumer surplus of $\frac{(v+\sigma-\gamma)^2}{2}$, whereas it generates a consumer surplus of $\frac{(v+\beta\cdot\sigma-\gamma)^2}{2}$ if the rival is ad-funded. The following proposition compares consumer surplus in the three different configurations.

Proposition 4 *Consumer surpluses in the different business model configurations compare as follows:*

- If $\sigma < \gamma$, $CS_{DD} > CS_{DA} > CS_{AA}$
- If $\gamma < \sigma < \frac{\gamma}{\beta}$, $CS_{DA} > CS_{DD} > CS_{AA}$
- If $\sigma > \frac{\gamma}{\beta}$, $CS_{AA} > CS_{DD}$ and $CS_{DA} > CS_{DD}$; furthermore the ranking between CS_{AA} and CS_{DA} varies wrt. the parameters.

Proof. See Appendix 7.4 ■

When both platforms are device-funded, consumers receive only the the stand-alone utility v from joining a platform. In the asymmetric configuration, the ad-funded platform is able to provide a higher surplus to its users than the stand-alone value, and

consequently serves a larger number of users, whenever $\sigma \geq \gamma$. Conversely, if $\sigma \leq \gamma$, the additional quality that the ad-funded platform can provide thanks to its investment does not compensate for the nuisance it imposes on users with ads, resulting in a lower consumer surplus than when both platforms are device-funded.

When both platforms are ad-funded, their incentives to invest are hindered by the competition in the advertising market, which is not at play with an asymmetric configuration. Consumer surplus is then higher in the configuration in which both platforms are ad-funded than in the configuration with two device-funded platforms if and only if $\gamma \leq \beta\sigma$.

As a result, users will always prefer the symmetric configuration with two device-funded platform when the value of an impression σ is relatively low, meaning that ad-funded platforms have low incentives to invest, or when the ad-nuisance is high.

Finally, the comparison between the configurations AD and AA is trickier and is detailed in Appendix 7.4. We can show that when a second impression on users is very discounted ($\beta \leq \frac{1}{2}$), competition on the advertising market in a symmetric configuration is so fierce that it reduces the incentives to invest for ad-funded platforms: in that case, users prefer an asymmetric setting. By contrast, if the discount is not so strong ($\beta \geq \frac{1}{2}$), the asymmetric setting is preferred by users only when the ad-funded business model is relatively less attractive to them, i.e. when the incentives for ad-funded platforms to invest are low (irrespective of the other platform's business model) or when the nuisance from advertising is high. Intuitively, if β is close to 1, as the value of an impression goes up for advertisers, ad-funded platforms become more and more attractive from the point of view of users, ultimately leading them to prefer that all of them adopt the same business model.

Figure 1 offers a visualisation of Proposition 4 by displaying the preferred configuration of consumers for some values of the parameters.

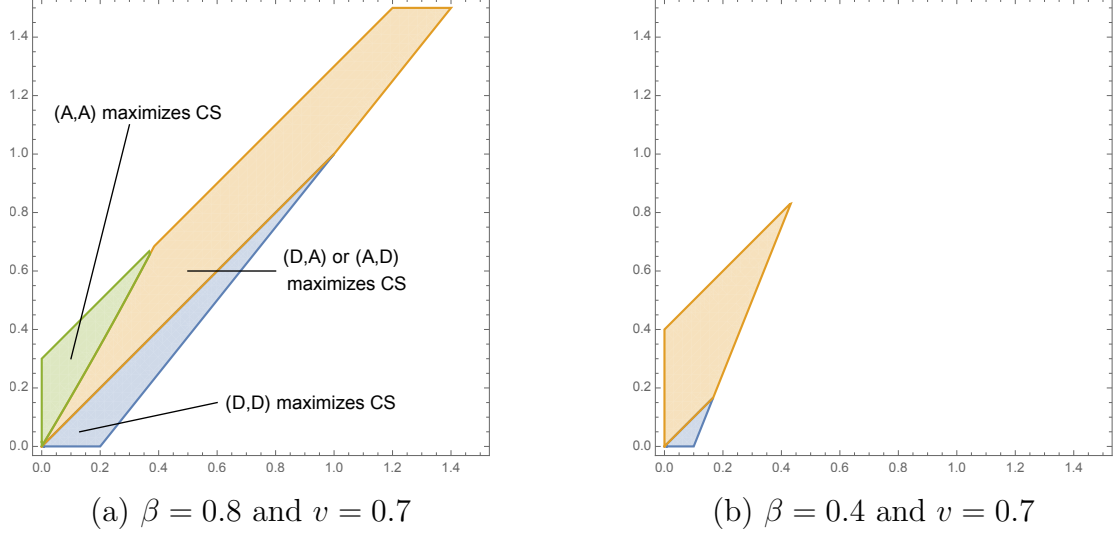


Figure 1: Consumer surplus maximizing configurations
x-axis = γ and y-axis = σ

4 Business model decisions

In this section, we analyze platforms' choices of business models (device-funded or ad-funded).

Consider first a platform's choice when its rival is device-funded.

Lemma 6 *The best response of a platform facing a device-funded rival is to be device- rather than ad-funded ($\pi_{DD} \geq \pi_{AD}$) whenever*

- *either the stand-alone value of the platform is large enough compared to the value of an ad ($v \geq \sigma(1 + \sqrt{2})$),*
- *or the ad-nuisance is strong ($v \leq \sigma(1 + \sqrt{2})$ and $\gamma \geq v + \frac{\sigma^2 - v^2}{2\sigma}$).*

Proof. The proof is straightforward and derives from the comparison of profits $\Pi_{AD} = \sigma \cdot (v + \sigma - \gamma) - \frac{\sigma^2}{2}$ and $\Pi_{DD} = \frac{v^2}{2}$. ■

We have shown in section 3 that being device-funded is always as profitable regardless of the other platform's business model ($\Pi_{DD} = \Pi_{DA}$). We know also that it is always more profitable to be an ad-funded platform when the other platform is device-funded rather than when it is ad-funded too ($\Pi_{AD} \geq \Pi_{AA}$).

From this we can derive the following proposition.

Proposition 5 (1) *Whenever $\Pi_{DD} \geq \Pi_{AD}$ there is a unique symmetric equilibrium, in which both platforms are device-funded.*

(2) *Otherwise,*

- (i) either $\Pi_{DD} \geq \Pi_{AA}$ and there are two mirror equilibria, in which one platform chooses to be device-funded while the rival chooses to be ad-funded,
- (ii) or $\Pi_{DD} \leq \Pi_{AA}$, and there is a unique equilibrium, in which both platforms choose to be ad-funded.

Proof.

(1) derives from $\Pi_{DA} = \Pi_{DD} \geq \Pi_{AD} \geq \Pi_{AA}$.

(2i) derives from $\Pi_{AA} \leq \Pi_{DA} = \Pi_{DD} \leq \Pi_{AD}$.

(2ii) derives from $\Pi_{DA} = \Pi_{DD} \leq \Pi_{AA} \leq \Pi_{AD}$.

■

We characterize the conditions under which the asymmetric equilibria prevail in Appendix 7.3. Figure 2 illustrates platforms' business model decisions in equilibrium in the plane (γ, σ) for two different sets of the parameters β and v .

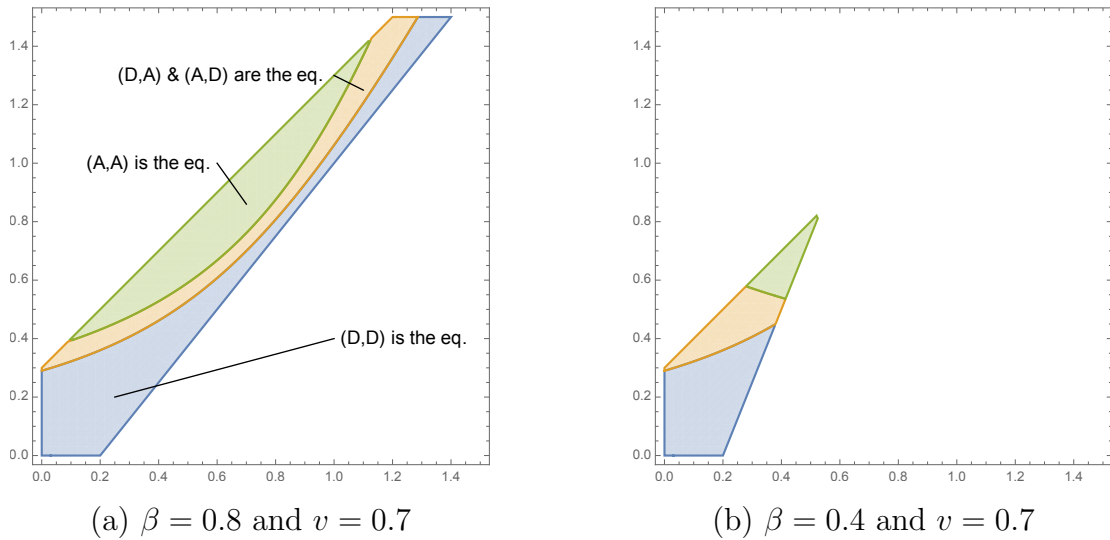


Figure 2: Business model decision: x-axis = γ and y-axis = σ

As we have seen in Lemma 6, both platforms choose to be device-funded whenever the value of an ad is low compared to the stand-alone value of the platform (σ low or v high), or when the ad-annoyance is strong (γ high) : it is then easier to monetize the service offered by the platforms to the users than to the advertisers. When σ is larger or γ lower, choosing the ad-funded business model becomes a more profitable option, especially when the rival does not choose to do so (as it grants the ad-funded platform a monopoly position on the advertising market). When β increases the asymmetric equilibrium become less likely.

Finally, we compare the equilibrium business model configuration to the business model configuration that would maximize consumer surplus.

Figure 3 highlights situations, in which endogenous business model decisions may be suboptimal from a consumer surplus perspective.

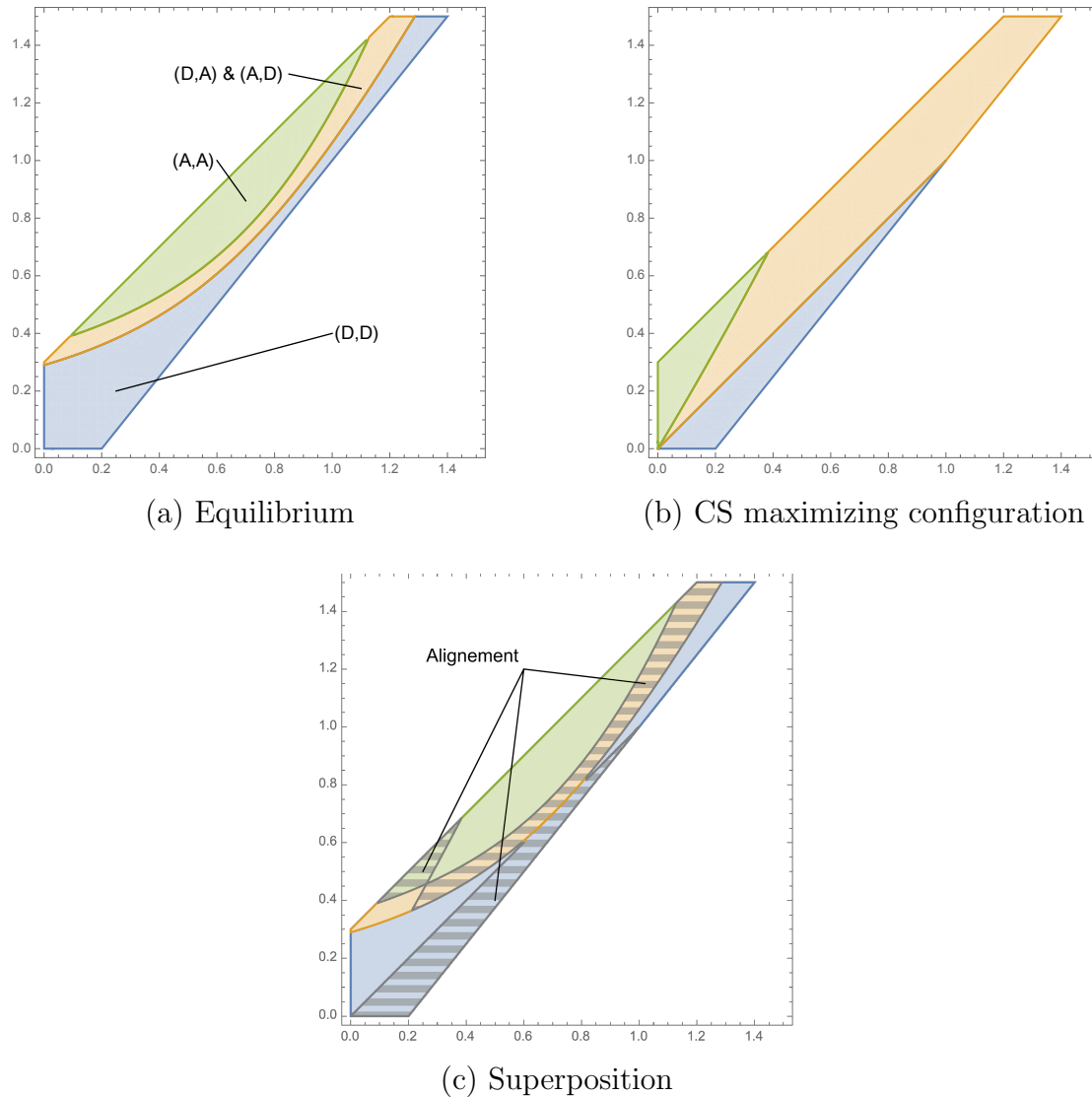


Figure 3: Equilibrium and CS maximizing configuration superposition ($\beta = 0.8, v = 0.7$)
x-axis = γ and y-axis = σ

Figure 3(c) highlights a misalignment between platforms' decisions and what would be preferred by users for some values of the parameters space. For instance, we can think about cases where $\gamma \notin [\underline{\gamma}, \bar{\gamma}]$, in which we know that the equilibrium will always be the symmetric configuration with two device-funded platforms. In those cases, we also know that for $\sigma > \gamma$, different configurations would be preferred, with at least one ad-funded platform.

In summary, we emphasize that platforms business model decisions may be an additional sources of distortion beyond pricing and investments.

5 Discussion: Market power in the adtech sector

The Competition and Markets Authority (2020) and the French Competition Authority⁶ have stressed the importance of protecting advertisers and publishers from Big Tech’s excessive market power. Smaller ad-funded platforms, or publishers, are usually not able to sell their advertising space directly to advertisers. They need to source their advertising technology from an *adtech* provider. Google has been found to be the dominant player by the French Competition Authority. The Competition and Markets Authority (2020) found that Google was able to take a commission rate on the publishers advertising revenue of approximately 35%.

Suppose that there is an *adtech* firm, which is able to extract a proportion $\tau \in [0, 1]$ of the ad-funded platforms’ advertising revenues: this translates in our setup into assuming that the ”perceived” value of an impression from the point of view of the publishers can be updated to $(1 - \tau) \cdot \sigma$. Stricter anti-trust policy to tackle Google’s dominance in the *adtech* would thus lead to a decrease in τ , thereby increasing the publishers perceived value of an impression. In our model, such a policy would thus translate into an increase in σ .

An increase in σ resulting from reduced *adtech* firms’ market power would affect the profitability of the ad-funded business model. It would, as a result, allow ad-funded platforms to invest more, benefiting their users. Considering the equilibrium in platforms’ decisions as fixed, including business models, this enhances total consumer surplus, as shown in Section 3.4. However, this policy might also have an influence on the business model decisions of platforms.

A policy leading to an increase in σ could have unintended effects on realised total consumer surplus. For example, consider that initially we have a set of parameters $(v, \beta, \gamma, \sigma) \in \mathcal{P}$ such that the equilibrium of the business model decision game is the asymmetric configuration $(\Pi_{AA}(v, \beta, \gamma, \sigma) \leq \Pi_{DD}(v, \beta, \gamma, \sigma) < \Pi_{AD}(v, \beta, \gamma, \sigma))$, and such that total consumer surplus is maximized by the asymmetric configuration. As specified earlier, an increase in σ by $\Delta\sigma > 0$ would increase the total consumer surplus, if the business models remain unchanged. However, it can be that after the implementation of the policy, the equilibrium changes to a configuration with two ad-funded platform $(\Pi_{AA}(\sigma + \Delta\sigma) > \Pi_{DD}(\sigma + \Delta\sigma))$, while the consumer surplus would still be maximized in an asymmetric setting. In such cases, the increased profitability of the ad-funded business model, which would usually induce higher investment, leads to a change in the business model configuration. Platforms choose to both be ad-funded and to compete on the advertising market, but the users are overall harmed by the policy as the platforms will overall invest less.

⁶See decision 21-D-11 from August 7, 2021, available at: [https://www.autoritedelaconcurrence.fr\[...\]](https://www.autoritedelaconcurrence.fr[...])

For example, let us consider a simple case, where $\beta < \frac{1}{2}$, in which we know from Proposition 4 that the configuration with two ad-funded platforms is never the consumer surplus maximizing configuration. Let us denote by $\sigma_{DD \rightarrow DA}$ such that $\Pi_{AD}(\sigma_{DD \rightarrow DA}) = \Pi_{DD}(\sigma_{DD \rightarrow DA})$ and $\sigma_{DA \rightarrow AA}$ such that $\Pi_{AA}(\sigma_{DA \rightarrow AA}) = \Pi_{DA}(\sigma_{DA \rightarrow AA})$. We know from Appendix 7.3, that $\sigma_{DA \rightarrow AA} > \sigma_{DD \rightarrow DA}$, and that we can characterize the equilibrium thanks to those thresholds. We will assume that our parameters are such that $\gamma, \sigma_{DD \rightarrow DA}, \sigma_{DA \rightarrow AA} \in]\sigma_{\min}, \sigma_{\max}[$ ⁷. Figure 4 can help visualize effect of policies influencing the profitability of some business models:

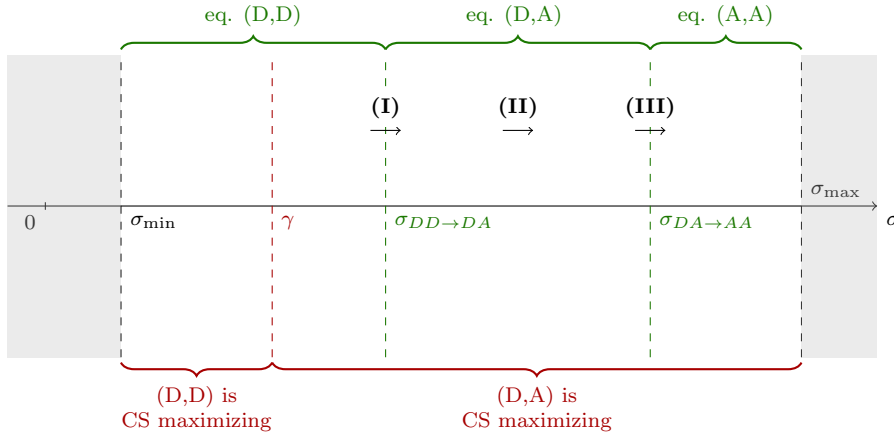


Figure 4: Policy Effects

Here, it is obvious that both (I) and (II) are going to be changes for the better. (I) would be a policy stimulating a consumer surplus enhancing change in equilibrium. (II) would not influence the equilibrium, platforms would keep the same business models, but the ad-funded would get higher revenue per user and thus invest more. However, (III) would be the kind of change with unintended effects we discussed above. In principle, it could lead to more investment as in (II), but the change in equilibrium would harm users.

So, to summarize, a regulator could credibly influence σ , through promoting fiercer competition in the *adtech* stack for instance. Any increase in σ would be *a priori* welcome, but a regulator should take into account platforms incentives to adapt and change their business model, which might lead to a different equilibrium, and mitigate the positive effects of such policy.

6 Conclusion

In this paper, we allow two platforms to choose their business models and invest in quality-enhancing investment. We aim to understand not only how a platform's business model

⁷Which happens for example when $\beta = 0.4$, $v = 0.6$ and $\gamma = 0.1$.

shapes its incentives to invest, but also how the business models of other platforms might influence these incentives. Additionally, we analyze platforms' business model decisions in equilibrium.

We find that quality investment is higher for a device-funded platform than for an ad-funded platform when the value of the service to consumers is higher than the value of exposing a marginal consumer to ads to advertisers. Furthermore, we analyze the equilibrium business model configuration. Unsurprisingly, when the *return to ads* is very low, platforms are better off if they are both device-funded, and when it is very high, both platforms prefer to be ad-funded. But asymmetric business model configurations can also arise in equilibrium. Indeed, in an asymmetric setting with differentiation in business models, there is no issue of overlapping viewership and hence no competition in the advertising market: the ad-funded platform enjoys a monopoly position on the entirety of its user base's viewership. This results in higher profitability for the ad-funded business model in such a setting compared to a symmetric setting where all platforms adopt the same business model. Consequently, there can be more investment from platforms in an asymmetric setting due to a greater ability to monetize it. This is a driving force towards the emergence of asymmetric equilibria, which can arise, despite the fact that platforms are identical *ex ante*. Platforms incentives may be misaligned with those of a user-surplus-maximizing social planner. We identify that business model decisions could induce some distortions, in addition to pricing and investments distortions.

Finally, we discuss the relevance of policies that could influence the profitability of one business model or another (such as targeted taxes and competition policy). We argue that while these can be effective tools to foster more investment from platforms, they could also alter the incentives to adopt one business model over another, potentially leading to unintended effects that ultimately make platform users worse off.

7 Appendices

7.1 Assumption 1 and parameter space

We want to ensure that in each configuration, in equilibrium, the market is covered and we have partial multi-homing. This requires that in equilibrium, we have $0 \leq \hat{x}_2 \leq \hat{x}_1 \leq 1$:

- In the device-funded vs. device-funded configuration, to ensure that \hat{x}_1 and \hat{x}_2 are within $[0, 1]$, we must assume that $0 \leq v \leq 1$. Furthermore, there is partial multi-homing in equilibrium if $\hat{x}_1 - \hat{x}_2 > 0$, which is satisfied whenever $v > 1/2$. So, we have to assume that $1/2 < v \leq 1$.
- In the asymmetric configuration, to ensure that \hat{x}_1 and \hat{x}_2 are within $[0, 1]$ in equilibrium, we must assume that $0 \leq v \leq 1$ and $\gamma - v \leq \sigma \leq 1 + \gamma - v$. Furthermore, there is partial multi-homing in equilibrium if $\hat{x}_1 - \hat{x}_2 > 0$, which is satisfied whenever $\sigma > 1 + \gamma - 2v$. So, we have to assume that $0 \leq v \leq 1$ and that $1 + \gamma - 2v < \sigma \leq 1 + \gamma - v$.
- In the ad-funded vs. ad-funded configuration, to ensure that \hat{x}_1 and \hat{x}_2 are within $[0, 1]$ in equilibrium, we must assume that $\frac{\gamma-v}{\beta} \leq \sigma \leq \frac{1+\gamma-v}{\beta}$. Furthermore, there is partial multi-homing in equilibrium if $\hat{x}_1 - \hat{x}_2 > 0$, which is satisfied whenever $\sigma > \frac{\frac{1}{2}+\gamma-v}{\beta}$. So, we have to assume that $\frac{1}{\beta} \cdot (\frac{1}{2} + \gamma - v) \leq \sigma \leq \frac{1}{\beta} \cdot (1 + \gamma - v)$.

As we need to make all the assumptions above, we end up assuming that $v \in [\frac{1}{2}, 1]$ and $\frac{1}{\beta} \cdot (\frac{1}{2} + \gamma - v) \leq \sigma \leq 1 + \gamma - v$ as in Assumption 1. From the set of assumptions made in Section 2 and Assumption 1, we can then define the parameter space as follows:

$$\mathcal{P} = \begin{cases} v \in [\frac{1}{2}, 1] \\ \beta \in [0, 1] \\ \gamma \geq 0 \\ \max\left(0, \frac{1}{\beta} \cdot (\frac{1}{2} + \gamma - v)\right) \leq \sigma \leq 1 + \gamma - v \end{cases} \subset \mathbb{R}^4.$$

7.2 Proof of Proposition 2

(a) First, we compare Π_{DD} to Π_{AD} (i.e., the profit of the ad-funded platform in configuration DA). We have:

$$\Pi_{AD} - \Pi_{DD} = \sigma(v + \sigma - \gamma) - \sigma^2/2 - v^2/2 = \frac{\sigma^2}{2} + \sigma(v - \gamma) - \frac{v^2}{2}.$$

Thus, $\Pi_{AD} > \Pi_{DD}$ if and only if $\sigma > \hat{\sigma}$, with

$$\hat{\sigma} \equiv \gamma - v + \sqrt{v^2 + (v - \gamma)^2}.$$

(b) Second, we prove that $\Pi_{AD} \geq \Pi_{AA}$. Note that if $\beta = 1$, we have $\Pi_{AD} = \Pi_{AA}$. Now, assume that $\beta < 1$. Note that

$$\Pi_{AD} = \sigma \cdot (v + \sigma - \gamma) - \frac{\sigma^2}{2} \geq \sigma \cdot \underbrace{(v + \beta \cdot \sigma - \gamma)}_{SH_{AA} + MH_{AA}} - \frac{\beta \cdot \sigma^2}{2},$$

as $\sigma = \underset{q}{\operatorname{argmax}} \sigma \cdot (v + q - \gamma) - \frac{q^2}{2}$. Moreover:

$$\Pi_{AA} = \sigma \cdot SH_{AA} + \beta \cdot \sigma \cdot MH_{AA} - \frac{(\beta \cdot \sigma)^2}{2} < \sigma \cdot (SH_{AA} + MH_{AA}) - \frac{(\beta \cdot \sigma)^2}{2},$$

which proves that $\Pi_{AD} \geq \Pi_{AA}$.

(c) Summing up, if $\sigma < \hat{\sigma}$, we have $\Pi_{DD} = \Pi_{DA} > \Pi_{AD} \geq \Pi_{AA}$. If $\sigma \geq \hat{\sigma}$, we have $\Pi_{AD} \geq \Pi_{DA} = \Pi_{DD}$ and $\Pi_{AD} \geq \Pi_{AA}$.

7.3 Characterization of equilibria with asymmetric business models

We seek to show that there are parameter values in our parameter space where platforms adopt different business models in equilibrium. We understand that if $\beta = 1$, asymmetric equilibrium cannot occur because there is no discounted second impression effect nor competition in the advertising market. In such cases, ad-funded platforms are indifferent to the other platform's business model, leading only to symmetric equilibria. Therefore, for the rest of this proof, we assume $\beta < 1$.

An asymmetric equilibrium arises if and only if platforms best responses are 1) to be ad-funded when the other platform is device-funded ($\Pi_{AD} > \Pi_{DD}$) 2) to be device-funded when the other platform is ad-funded ($\Pi_{DA} > \Pi_{AA}$).

Consider any $(v, \gamma, \beta, \sigma)$ in our parameter space. First, we can easily show that:

- $\frac{d\Pi_{DD}}{d\sigma} = \frac{d\Pi_{DA}}{d\sigma} = 0$
- $\frac{d\Pi_{AD}}{d\sigma} > 0$
- $\frac{d\Pi_{AA}}{d\sigma} > 0$ (note that we assume $\beta < 1$)
- $\Pi_{AD} > \Pi_{AA}$

The strict monotonicity of both ad-funded profits, combined with the fact that device-funded profits are constant in σ , implies there exist at most a unique solution to $\Pi_{AD} = \Pi_{DD}$ and to $\Pi_{AA} = \Pi_{DA}$

To simplify our notations, let us define:

$$f : \begin{cases} [\sigma_{\min}, \sigma_{\max}] & \longrightarrow \mathbb{R} \\ \sigma & \longmapsto \Pi_{AD}(\sigma) - \frac{v^2}{2} \end{cases}$$

and

$$g : \begin{cases} [\sigma_{\min}, \sigma_{\max}] & \longrightarrow \mathbb{R} \\ \sigma & \longmapsto \Pi_{AA}(\sigma) - \frac{v^2}{2} \end{cases}$$

With $\frac{v^2}{2} = \Pi_{DD} = \Pi_{DA}$.

We can thus write more simply that, for $(v, \gamma, \beta, \sigma) \in \mathcal{P}$ the equilibrium is asymmetric if and only if $f(\sigma) > 0 > g(\sigma)$. From above, we have that $f'(\cdot) > 0$, $g'(\cdot) > 0$ and $f > g$.

For any (v, γ, β) in our parameter space, there exists a pair of asymmetric equilibria $(D, A$ and $A, D)$ if and only if there exist a $\sigma \in [\sigma_{\min}, \sigma_{\max}]$ such that $f(\sigma) > 0 > g(\sigma)$. A necessary and sufficient condition for this is $f(\sigma_{\max}) > 0$ and $g(\sigma_{\min}) < 0$.

Let us first start by analyzing when $f(\sigma_{\max}) > 0$, meaning when there exist a σ in our parameter space such that being ad-funded can be a best response to the other platform being device-funded i.e. being ad-funded is not a strictly dominated strategy for any σ .

Consider any (v, γ, β) in our parameter space. We have that $\sigma_{\max} = 1 - (v - \gamma)$, and it is the value of σ such that the equilibrium demand for an ad-funded platform in an asymmetric setup, $v + \sigma - \gamma$, equals 1. We have $\Pi_{AD}(\sigma_{\max}) = \sigma_{\max} \cdot 1 - \frac{\sigma_{\max}^2}{2}$. Hence, $f(\sigma_{\max}) = \sigma_{\max} - \frac{\sigma_{\max}^2}{2} - \frac{v^2}{2}$.

$$\begin{aligned} f(\sigma_{\max}) > 0 &\Leftrightarrow \sigma_{\max} \in \left] 1 - \sqrt{1 - v^2}, 1 + \sqrt{1 - v^2} \right[\\ &\Leftrightarrow \gamma \in \left] \underbrace{v - \sqrt{1 - v^2}}_{\equiv \gamma}, \underbrace{v + \sqrt{v - v^2}}_{\equiv \bar{\gamma}} \right[, \end{aligned}$$

with

$$\begin{aligned} \gamma &\equiv v - \sqrt{1 - v^2} \\ \bar{\gamma} &\equiv v + \sqrt{1 - v^2}. \end{aligned}$$

Now, let us analyze when $g(\sigma_{\min}) < 0$. Verifying this condition implies that there exist a σ in our parameter space such that being device-funded can be a best response to an ad-funded platform i.e. being device-funded is not a strictly dominated strategy for any σ .

Consider any (v, γ, β) in our parameter space. We have

$$\sigma_{\min} = \max \left(0, \frac{1}{\beta} \left(\frac{1}{2} - (v - \gamma) \right) \right)$$

Suppose first that $\gamma \leq v - \frac{1}{2}$, which implies that $\sigma_{\min} = 0$: then $\Pi_{AA} = 0 < \Pi_{DA}$ and

$g(\sigma_{\min}) < 0$.

Suppose instead that $\gamma > v - \frac{1}{2}$, hence $\sigma_{\min} = \frac{1}{\beta} \left(\frac{1}{2} - (v - \gamma) \right)$. We have thus $\Pi_{AA}(\sigma_{\min}) = \frac{\sigma_{\min}}{2} - \frac{(\beta \cdot \sigma_{\min})^2}{2}$ and $g(\sigma_{\min}) = \frac{\sigma_{\min}}{2} - \frac{(\beta \cdot \sigma_{\min})^2}{2} - \frac{v^2}{2}$. We distinguish two cases:

- If $\beta > \frac{1}{2v}$, then one can easily verify that for all γ , $g(\sigma_{\min}) < 0$.
- If not, then:

$$g(\sigma_{\min}) < 0 \Leftrightarrow \sigma_{\min} \notin \left[\frac{1 - \sqrt{1 - (2\beta \cdot v)^2}}{2}, \frac{1 + \sqrt{1 - (2\beta \cdot v)^2}}{2} \right]$$

$$\Leftrightarrow \gamma \notin \left[\underbrace{v - \frac{1}{2} + \frac{1}{2} \cdot \left(\frac{1}{\beta} - \sqrt{\frac{1}{\beta^2} - (2v)^2} \right)}_{\equiv \underline{\gamma}'}, \underbrace{v - \frac{1}{2} + \frac{1}{2} \cdot \left(\frac{1}{\beta} + \sqrt{\frac{1}{\beta^2} - (2v)^2} \right)}_{\equiv \bar{\gamma}'} \right],$$

where

$$\underline{\gamma}' \equiv v - \frac{1}{2} \cdot \left(\frac{1}{\beta} - 1 - \sqrt{\frac{1}{\beta^2} - (2v)^2} \right) > v - \frac{1}{2}$$

$$\bar{\gamma}' \equiv v - \frac{1}{2} \cdot \left(\frac{1}{\beta} - 1 + \sqrt{\frac{1}{\beta^2} - (2v)^2} \right)$$

To sum up, we have shown that, in our parameter space, there exists an interval $I \neq \emptyset$ and $I \subset [\sigma_{\min}, \sigma_{\max}]$ such that for any $(v, \gamma, \beta, \sigma)$ with $\sigma \in I$, an asymmetric equilibrium exists if and only if:

- either $\beta > \frac{1}{2v}$ and $\gamma \in]\underline{\gamma}, \bar{\gamma}[$
- or $\beta \leq \frac{1}{2v}$ and $\gamma \in]\underline{\gamma}, \underline{\gamma}'[\cup]\bar{\gamma}', \bar{\gamma}[$

To be more precise, in both cases, an asymmetric equilibrium exists for intermediate values of σ . Let us denote by $\sigma_{DD \rightarrow DA}$ the value of an impression such that $\Pi_{AD}(\sigma_{DD \rightarrow DA}) = \Pi_{DD}(\sigma_{DD \rightarrow DA})$ i.e. $f(\sigma_{DD \rightarrow DA}) = 0$, and $\sigma_{DA \rightarrow AA}$ such that $\Pi_{AA}(\sigma_{DA \rightarrow AA}) = \Pi_{DA}(\sigma_{DA \rightarrow AA})$ i.e. $g(\sigma_{DA \rightarrow AA}) = 0$. We know from Proposition 5 that $\sigma_{DD \rightarrow DA} < \sigma_{DA \rightarrow AA}$ and by definition the conditions for an asymmetric equilibrium to arise would be verified for $\sigma \in [\sigma_{DD \rightarrow DA}, \sigma_{DA \rightarrow AA}]$. Denoting $\underline{\sigma} \equiv \max(\sigma_{DD \rightarrow DA}, \sigma_{\min})$ and $\bar{\sigma} \equiv \min(\sigma_{DA \rightarrow AA}, \sigma_{\max})$, we have shown that symmetric equilibria exist for $\sigma \in [\underline{\sigma}, \bar{\sigma}]$.

Summary Consider any $(v, \beta, \gamma, \sigma)$ in our parameter space. Given the thresholds and quantities introduced above, we can characterize the final equilibria of our game as follows.

- if $\beta \geq \frac{1}{2v}$ and,
 - $\gamma \notin]\underline{\gamma}, \bar{\gamma}[$, the unique equilibrium is (D,D)

- $\gamma \in [\underline{\gamma}, \bar{\gamma}]$ and,
 - * $\sigma < \underline{\sigma}$, the unique equilibrium is (D,D)
 - * $\sigma \in [\underline{\sigma}, \bar{\sigma}]$, the equilibria are (D,A) and (A,D)
 - * $\sigma > \bar{\sigma}$, the unique equilibrium is (A,A)
- if $\beta < \frac{1}{2v}$ and,
 - $\gamma \notin [\underline{\gamma}, \bar{\gamma}]$, the unique equilibrium is (D,D)
 - $\gamma \in [\underline{\gamma}, \underline{\gamma}'] \cup [\bar{\gamma}', \bar{\gamma}]$ and,
 - * $\sigma < \underline{\sigma}$, the unique equilibrium is (D,D)
 - * $\sigma \in [\underline{\sigma}, \bar{\sigma}]$, the equilibria are (D,A) and (A,D)
 - * $\sigma > \bar{\sigma}$, the unique equilibrium is (A,A)
 - $\gamma \in]\underline{\gamma}', \bar{\gamma}'[$, the unique equilibrium is (A,A)

7.4 Consumer surplus comparison

We want to compare total consumer surplus in the three different business model configurations. As a reminder, note that:

$$\begin{aligned}
 CS_{DD} &= v^2 \\
 CS_{DA} &= \frac{(v + \sigma - \gamma)^2}{2} + \frac{v^2}{2} \\
 CS_{AA} &= (v + \beta \cdot \sigma - \gamma)^2
 \end{aligned}$$

Note first that we have $CS_{DA} \geq CS_{DD} \Leftrightarrow \sigma \geq \gamma$ and $CS_{AA} \geq CS_{DD} \Leftrightarrow \beta \cdot \sigma \geq \gamma$. Moreover, note that if $\beta \cdot \sigma < \gamma$, we have that $CS_{DA} > CS_{AA}$. This implies that we have:

- If $\sigma < \gamma$, $CS_{DD} > CS_{DA} > CS_{AA}$
- If $\gamma < \sigma < \frac{\gamma}{\beta}$, $CS_{DA} > CS_{DD} > CS_{AA}$
- If $\sigma > \frac{\gamma}{\beta}$, $CS_{AA} > CS_{DD}$ and $CS_{DA} > CS_{DD}$

For $\sigma > \frac{\gamma}{\beta}$, three cases need to be considered in order to compare CS_{DA} and CS_{AA} . 1) $\beta \leq \frac{1}{2}$, 2) $\beta \in]\frac{1}{2}, \frac{1}{\sqrt{2}}[$, 3) $\beta \geq \frac{1}{\sqrt{2}}$. By studying the sign of the difference in total consumer surplus $\Delta CS = CS_{DA} - CS_{AA}$, we can show that:

1) If $\beta < \frac{1}{2}$, $CS_{DA} > CS_{AA} > CS_{DD}$

2) If $\frac{1}{2} < \beta < \frac{1}{\sqrt{2}}$:

$$\text{- If } \gamma > \tilde{\gamma} \equiv v \cdot \left(1 - \sqrt{\frac{1-2\beta^2}{2}} \cdot \frac{1}{1-\beta} \right), CS_{DA} > CS_{AA} > CS_{DD}$$

- If $\gamma < \tilde{\gamma}$, if $\sigma \in \left[\frac{(v-\gamma)\cdot(2\beta-1)-\sqrt{\Delta}}{1-2\beta^2}, \frac{(v-\gamma)\cdot(2\beta-1)+\sqrt{\Delta}}{1-2\beta^2}\right]$, $CS_{AA} > CS_{DA} > CS_{DD}$.
Else, $CS_{DA} > CS_{AA} > CS_{DD}$.

3) If $\beta > \frac{1}{\sqrt{2}}$:

- If $\sigma < \frac{(v-\gamma)\cdot(2\beta-1)-\sqrt{\Delta}}{1-2\beta^2}$, $CS_{DA} > CS_{AA} > CS_{DD}$
- Else, $CS_{AA} > CS_{DA} > CS_{DD}$

$$\text{With } \Delta \equiv (v - \gamma)^2 \cdot (1 - 2\beta)^2 - (1 - 2\beta^2) \cdot (v^2 - (v - \gamma)^2).$$

1) $\beta < \frac{1}{2}$. We can show that for any $\beta < \frac{1}{2}$, $CS_{DA} < CS_{AA}$.

Consider any γ and v in the parameter space. We can easily show that, by definition of σ_{\min} , $CS_{DA}(\sigma_{\min}) \geq CS_{AA}(\sigma_{\min})$, meaning that for the lowest value of σ possible in our parameter space, $\Delta CS(\sigma_{\min}) \geq 0$. Moreover, we can show that for all $\sigma \in [\sigma_{\min}, \sigma_{\max}]$, $\frac{\partial \Delta CS}{\partial \sigma} > 0$.

This implies that for any $\beta < \frac{1}{2}$, $\gamma > 0$ and $v \in [\frac{1}{2}, 1]$, total consumer surplus is larger in the asymmetric setting for the lowest possible value of σ . We can show that this gap increases in σ , hence always leading to $CS_{DA} > CS_{AA}$ for any $\beta < \frac{1}{2}$.

2) $\beta \in \left] \frac{1}{2}, \frac{1}{\sqrt{2}} \right[$. We can show that for $\beta \in \left] \frac{1}{2}, \frac{1}{\sqrt{2}} \right[$ and $\gamma > \tilde{\gamma}$, $CS_{DA} > CS_{AA}$. When $\gamma < \tilde{\gamma}$, $CS_{AA} < CS_{DA}$ if and only if $\sigma \in [\underline{\sigma}', \bar{\sigma}']$.

Assume $\beta \in \left] \frac{1}{2}, \frac{1}{\sqrt{2}} \right[$. Consider any γ and v in the parameter space. We have that:

$$\begin{aligned} \Delta CS &= CS_{AD} - CS_{AA} \\ &= \sigma^2 \cdot \frac{1 - 2\beta^2}{2} + \sigma \cdot (v - \gamma) \cdot (1 - 2\beta) + \frac{v^2 - (v - \gamma)^2}{2} \end{aligned}$$

It follows that the difference in consumer surplus can be expressed as second order polynomial of σ . By computing the second order derivative w.r.t. σ of ΔCS , we can see that it is positive hence this function is convex in σ .

By looking at the discriminant of this second order polynomial, and more precisely at its sign, we can show that it is negative for $\gamma \in \left[v \cdot \left(1 - \sqrt{\frac{1-2\beta^2}{2}} \cdot \frac{1}{1-\beta} \right), v \cdot \left(1 + \sqrt{\frac{1-2\beta^2}{2}} \cdot \frac{1}{1-\beta} \right) \right]$, which implies that in this region, we have that $CS_{DA} \geq CS_{AA}$ for all σ .

Moreover, assume now that $\gamma > v \cdot \left(1 + \sqrt{\frac{1-2\beta^2}{2}} \cdot \frac{1}{1-\beta} \right) (> v)$. One can show as in 1) that:

- $\Delta CS(\sigma) \geq 0$
- $(\Delta CS)' > 0$ for all σ in our parameter space

Hence, $CS_{DA} > CS_{AA}$.

We thus have that for any $\beta \in \left] \frac{1}{2}, \frac{1}{\sqrt{2}} \right[$, any $\gamma > v \cdot \left(1 - \sqrt{\frac{1-2\beta^2}{2}} \cdot \frac{1}{1-\beta} \right) \equiv \tilde{\gamma}$, and any v and σ in our parameter space, $CS_{DA} > CS_{AA}$ i.e. the asymmetric configuration yields higher total consumer surplus than the configuration with two ad-funded platforms.

Now let us consider cases where $\gamma < \tilde{\gamma}$. If so, we have that the discriminant of ΔCS is positive and can be expressed as follows:

$$\Delta = (v - \gamma)^2 \cdot (2\beta - 1)^2 - (1 - 2\beta^2) \cdot (v^2 - (v - \gamma)^2)$$

It follows from this and ΔCS 's convexity in σ that $CS_{AA} \geq CS_{DA}$ if and only if $\sigma \in [\underline{\sigma}', \bar{\sigma}']$ with:

$$\underline{\sigma}' = \frac{(v - \gamma) \cdot (2\beta - 1) - \sqrt{\Delta}}{1 - 2\beta^2}$$

$$\bar{\sigma}' = \frac{(v - \gamma) \cdot (2\beta - 1) + \sqrt{\Delta}}{1 - 2\beta^2}$$

To sum up, for any $\beta \in \left] \frac{1}{2}, \frac{1}{\sqrt{2}} \right[$ and any v in our parameter space, we have that:

- for any $\gamma > \tilde{\gamma}$ and for any σ in our parameter space, $CS_{DA} > CS_{AA}$.
- for any $\gamma < \tilde{\gamma}$, $CS_{AA} > CS_{DA}$ if and only if $\sigma \in [\underline{\sigma}', \bar{\sigma}']$.

3) $\beta > \frac{1}{\sqrt{2}}$. We can show that for any $\beta > \frac{1}{\sqrt{2}}$, any γ and any v in our parameter space, $CS_{DA} > CS_{AA}$ if and only if $\sigma < \underline{\sigma}'$.

With $\beta > \frac{1}{\sqrt{2}}$, ΔCS 's discriminant is positive. One can also check that ΔCS is a concave function of σ . From this we get that $CS_{DA} \geq CS_{AA}$ if and only if $\sigma \in [\bar{\sigma}', \underline{\sigma}']$ and we can show that $\bar{\sigma}' < \underline{\sigma}'$. Which means that in our parameter space, for $\beta > \frac{1}{\sqrt{2}}$, $CS_{DA} > CS_{AA}$ if and only if $\sigma < \underline{\sigma}'$.

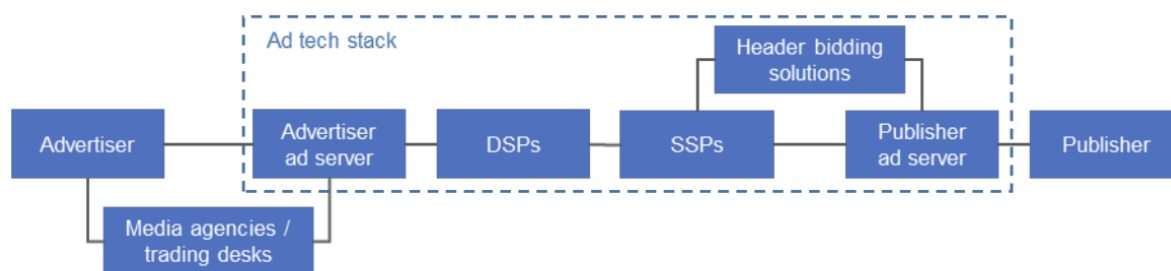
Chapter 2

Vertical Integration in Online Display Advertising, *AdTech* Contestability, and Advertising Restrictions

1 Introduction

In the digital economy, firms rely heavily on advertising to generate revenues. For instance, it is at the core of the monetization strategy of some Big Tech companies like Facebook or Google. These companies often function as gatekeepers, exerting control over significant streams of revenue and information on the internet. This situation has sparked concerns regarding potential anti-competitive behaviors in which they might engage.

The Competition and Markets Authority (2020) released a report about online advertising, providing a detailed analysis of both *search* and *display* advertising. Search advertising designates a type of advertising where sponsored links appear in response to a user's search query (de Cornière, 2016). Display advertising, on the other hand, involves static or video ads shown alongside content users are engaging with. The Competition and Markets Authority (CMA) report notably investigates Google's market dominance within the *adtech* stack, which refers to the chain of intermediaries between advertisers and ad publishers in the online display advertising market (see Figure 1). An advertiser is an entity (e.g., a firm) that seeks to display an ad to some potential consumers, while an ad publisher is an entity offering ad space for sale.



Source: CMA.

Figure 1: The *adtech* stack
(Source: CMA, 2020, p265)

According to interviews conducted by the CMA, there is a significant trend towards vertical integration within the *adtech* stack, as well as a considerable market concentration. The CMA notes: "The case of Google is noteworthy because not only does it operate along the entire value chain, but it also has the largest market shares among providers at each level of the chain" (p.271). This market structure can legitimately raise some concerns about the state of competition on the market.

The CMA is not the only competition authority or law enforcer to express concerns about Google's dominance in the *adtech* stack. These concerns are also echoed by the French Competition Authority, as in 2021, they imposed a 220 million euros fine on Google for abusing its dominant position within the *adtech* stack due to multiple anti-competitive practices¹. Furthermore, the Department of Justice of the United States of America (US DOJ) is currently pursuing a legal case against Google, alleging an even more extensive list of anti-competitive violations leading them to monopolize the market².

Google's conducts to try to prevent the emergence of competitors in the *adtech* stack are starting to be more and more acknowledged. According to the French Competition Authority¹, these efforts have manifested as limited interoperability with competitors' services in certain aspects of the *adtech* stack, along with preferential pricing, leading to very high switching costs for publishers and advertisers.

If Google's dominant position and anti-competitive conducts in the *adtech* stack are worrisome according to various competition authorities, its downstream position with YouTube may also as well be a powerful tool to prevent the emergence of competitors in the *adtech*. Following this lead, the CMA's examination extends beyond Google's dominance within the *adtech* stack alone and encompasses Google's influence in the realm of display advertising, primarily through its YouTube platform. They state: "[Google] also has a strong position in display advertising [...] through its YouTube platform" (p. 280) and go on to explain: "Google can leverage the importance of YouTube to augment

¹See decision no. 21-D-11 available at: https://www.autoritedelaconcurrence.fr/sites/default/files/-integral_texts/2021-06/21d11_0.pdf

²See the complaint filed on January 24, 2023, available at : <https://www.justice.gov/opa/press-release/file/1563746/dl>

its market power...” (p. 280).

An interesting example is the online news industry. Similar to many other online industries that depend on online display advertising, Google serves as the primary provider of advertising technologies for online news outlets such as newspapers and personal blogs. Major players like *The Guardian* in the United Kingdom, *Le Monde* in France, and *El País* in Spain all use Google’s services to display ads to their readership³. Furthermore, Google not only acts as the main provider for firms in this industry but also is a direct competitor, as YouTube has become a source of information for many citizens. Peitz and Reisinger (2015) emphasize this new role of Google’s video platform: “YouTube started out providing short amateur videos, which could be considered pure entertainment and outside the media world. However, nowadays, YouTube can be seen as a source of information that functions like media.”. In this specific industry, as in many others, Google plays a dual role, serving as both the advertising technology provider for its competitors and a direct competitor itself. This situation raises legitimate concerns about how the vertical relations at stake may influence market outcomes. While it seems that foreclosure may not be an issue given Google’s widespread provision of its services, questions arise about whether Google can potentially leverage its downstream position. If so, in what ways might this occur?

This concern regarding Google’s capacity to leverage its downstream position with YouTube will be the central focus of this paper. We aim to assess whether integration with a downstream display advertising platform can enhance the market power of an *adtech* stack incumbent.

In this paper, we construct a model that takes into account vertical relations within the display advertising market. We examine two two-sided platforms, or publishers, which offer content (e.g., news) to their users. Their revenue come from advertising, as they display ads to their respective consumer bases and, as a result, compete for consumer attention. However, since these platforms generate their revenue exclusively from advertising, they must exercise caution regarding the quantity of ads they display, as advertising is a nuisance to their consumers.

We make the assumption that these platforms do not own their advertising technology and must rely on an *adtech* stack intermediary to access advertisers and offer their ad space.⁴ Within this context, we analyze the presence of an incumbent within the *adtech* stack, which faces the threat of entry of a more efficient entrant. Here, efficiency refers to better targeting of ads for example, or any aspect that allows platforms to charge higher prices to advertisers for ad-space. We consider only a more efficient entrant because our purpose is to study the *adtech* stack’s contestability and to analyze whether there may

³This information can be verified by visiting these newspapers’ websites and inspecting the management of their ads. Last accessed on August 12, 2024.

⁴This is a relevant assumption in the context of news, for instance. Indeed, even major online news outlets do not have the technology to be able to offer their ad space directly to advertisers.

be excessive barriers to entry or not. Entry from less efficient players is not something a competition authority or a regulator would be interested in, as it would not be desirable⁵.

To investigate the ability of an *adtech* stack incumbent to exploit a downstream position in the market for consumer attention, we will explore two scenarios: one with a separated incumbent and another with an integrated incumbent.

Our findings align with the CMA’s assertion, suggesting that integration with a downstream platform empowers the incumbent to leverage its new position effectively, making entry deterrence more feasible and increasing its market power. This is achieved through two main effects: market size reduction from the entrant’s perspective, and a *collusive effect* of integration, softening competition for consumer attention, ultimately exposing them to higher levels of advertising. In conclusion, such vertical mergers in the display advertising market could be unilaterally detrimental to consumers.

However, the social planner is not unequipped to deal with the situation. Similar to restrictions already in place in the EU regarding the duration of commercial breaks on TV, we could imagine limiting consumers’ exposure to ads online. We consider potential imperfections in the implementation of such regulation, and discuss the effects of both strict and lenient restrictions.

Our paper relates to two strands of literature, namely the literature on vertical integration and the literature on advertising funded platforms.

The first strand of literature analyzes the competitive effects of vertical integration. While horizontal mergers tend to be anti-competitive, it is not so clear for vertical ones. There have been conflicting evidences of pro and anti-competitive effects of vertical integration (see, e.g., Rey and Tirole, 2007; Riordan, 2005). Vertical mergers can have pro-competitive effects, primarily by eliminating the double marginalization problem (Spengler, 1950). However, vertically integrated firms could also have incentives to engage in anti-competitive behaviors, such as market foreclosure or raising rivals’ costs (Salinger, 1988; Hart and Tirole, 1990; Ordober, Saloner and Salop, 1990*b*). The focus of this paper more closely aligns to Chen (2001)’s, as we identify similar *collusive effects* of integration, which, in turn, can prompt an unintegrated downstream firm to ”make a deal with the devil”, ultimately resulting in the eviction of the potential entrant.

The second strand of literature to which we relate analyzes multi-sided platforms. Seminal papers by Caillaud and Jullien (2003), Rochet and Tirole (2003), and Armstrong (2006) have provided normative and analytic tools to better define two-sided platforms and understand their pricing structures. In the spirit of Anderson and Coate (2005), we introduce indirect network effects between two groups (advertisers and consumers), adding a vertical dimension. Additionally, our work is closely related to de Cornière and Taylor (2014), as we consider the hybrid nature of dominant firms in digital advertising.

⁵In our model, we could allow for the entrant to be less efficient. It would not be able to enter the market or exert any competitive pressure on the incumbent.

However, we do not focus on the bias in search but rather on the effect of integration on online advertising markets contestability.

In summary, this paper addresses the anti-competitive effects of integration, considering various pricing and non-pricing strategies that platforms use to manage indirect network effects. We also discuss how extending European law to online display advertising, at least on some platforms, could resolve some issues related to the type of integration we consider.

We present our paper in the following six sections. In Section 2, we present the model. In Section 3, we study the case of a separated incumbent, and then, in Section 4, compare it with the integrated incumbent. In Section 5 we present two robustness checks we conducted. In Section 6, we analyze the effect of policy capping the online advertising levels. Finally, we provide concluding remarks in Section 7.

2 Model set-up

We study a model with two display advertising platforms competing downstream for consumer attention, deciding on their advertising level *i.e.* the quantity of available ad space they ultimately want to supply to advertisers. However, these platforms do not own their advertising technology (demand-side and supply-side platforms, bidding solutions etc.). Instead, they rely on services provided by an *adtech* stack firm, which appropriates an endogenous proportion of their advertising revenues. The *adtech* stack is composed of an incumbent and a potential entrant.

We examine two scenarios. Initially, we assume that the *adtech* stack incumbent is separated from any downstream platform. Subsequently, we explore the scenario where the incumbent acquires one of the downstream platforms to analyze the impact on competition within the AdTech stack and the display advertising market resulting from such an acquisition.

In the following, we introduce the four types of agents and their decisions.

Adtech stacks. A crucial component of this model is the so-called *adtech* stack. As introduced in the previous section, this *adtech* stack encompasses a complex chain of intermediaries. For a display advertising platform to reach advertisers, it must resort to using an *adtech* stack service. Essentially, one could view these *adtech* stack firms as providers of advertising technology to the display advertising platform.⁶

We make some simplifying assumptions to create a tractable model. According to the CMA's investigations, there is a strong tendency for vertical integration in this industry,

⁶Note that we do not allow downstream display advertising platforms to consider developing and deploying their own advertising technology to bypass existing *adtech* stacks (Bloch and Gautier, 2017). We consider that the cost of developing this technology would be too high for a publisher.

meaning that a firm is usually present at each part of the value chain. For instance, Google has acquired or developed advertiser ad servers and demand-side platforms (such as Google Ads, Display & Video 360), as well as some supply-side platforms, bidding solutions, and publisher ad servers (like Google Ad Manager, Ad Exchange and DoubleClick for Publishers). Following these observations, we will assume that *adtech* stacks can be considered as a single entity and not as a chain of intermediaries. Moreover, we will make a simplifying assumption about their pricing: we assume that an *adtech* stack takes a commission rate on the advertising revenues of display advertising platforms using its services. This is in line with the analysis done by the Competition and Markets Authority (2020). Using bidding data, the CMA estimates that this commission is approximately of 30% of advertisers' spending.

Following these assumptions, let us now introduce the two *adtech* stacks.

***Adtech* stack incumbent.** The *adtech* stack incumbent, which we denote as I takes a commission α_I on the advertising revenues of the platform(s) who decide to use its services, with $0 \leq \alpha_I \leq 1$. We assume that it does not price-discriminate between the platforms.

It has an advertising technology which allows it to offer a value of an impression $k > 0$ to advertisers. This parameter can capture the level of accuracy of targeting of the advertising technology that can influence conversion rates.

***Adtech* stack entrant.** The *adtech* stack entrant, which we denote as E , takes a commission α_E on the advertising revenues of the platform(s) which decide to use its services, conditional on entry. We assume that it does not price-discriminate between the platforms as well.

The entrant has a superior advertising technology to that of the incumbent (e.g. better targeting) which allows it to offer a value of an impression $k(1 + \Delta)$ to advertisers, with $\Delta \geq 0$. If we consider that the entrant is better at targeting ads, it will result in a higher value for an impression as it may lead to a higher conversion rate for advertisers.

The entrant has to pay an entry cost $e \geq 0$ to become active in the *adtech* market. This cost can capture the cost incurred for developing an advertising technology, the cost of qualified labor such as engineers, acquiring data to train its algorithms etc.⁷

Platforms. We consider two competing platforms (or publishers), denoted as P_1 and P_2 , that are both ad-financed. These two platforms compete downstream for consumer attention, within the display advertising market. Their primary objective is to attract as many eyeballs as possible to their respective platforms. Both platforms offer consumers

⁷Apple appears for example to be pursuing this objective and investing in developing its own *adtech* stack, see [https://digiday.com/media-buying/apples-expanding-ad-ambitions\[...\]](https://digiday.com/media-buying/apples-expanding-ad-ambitions[...)

content (such as news, videos, podcasts, etc.) of the same quality, providing users with a baseline utility of using their platform, denoted as $v > 0$. Access to the platforms is provided to consumers for free, and their revenues are solely derived from advertising. It is assumed that the platforms offer content to consumers at zero marginal cost.

We could think about them as any platform, funded by advertising, that brings content to its users in exchange for their attention, that they monetize through display advertising: newspapers, video sharing platforms, social media etc.

Platforms offer advertisers the opportunity to run an ad campaign, which involves the platform displaying an advertiser's ad to each of its consumers. Platform $P_i \in \{P_1, P_2\}$ determines the advertising campaign price p_i .

Platforms compete for consumer attention via their choices of ad level, which is denoted by $0 \leq a_i \leq 1$ for $i \in \{1, 2\}$. We denote as n_i^C consumer demand for platform $i \in \{1, 2\}$. We assume that ad space is provided at zero marginal cost. When a_i is low, it indicates that there is few ad space offered on platform P_i , leading to a high perceived quality for consumers due to an enhanced user experience. However, it is essential to note that providing this low ad level to consumers deprives the platforms of advertising revenues since there is less ad space available for sale.

Platforms cannot access advertisers directly, as they lack the infrastructure required to effectively do so. Instead they use an *adtech* stack to offer their advertising space. The *adtech* stack can be in two states: either it is monopolized by the incumbent, or, the entrant has entered, and platforms contemplate offering their ad space through one of the two available services. In the first case, where the upstream market is monopolized, a platform uses the incumbent's service (if the commission is not prohibitive). In the second case, it utilizes the service that allows it to maximize profit. In the event of equal profits, the platform opts for the most efficient *adtech* stack, namely that of the entrant.

Consider Platform P_i for $i \in \{1, 2\}$, which uses *adtech* stack $S \in \{I, E\}$. Its profit writes:

$$\Pi_i = (1 - \alpha_S) \cdot a_i \cdot p_i$$

Advertisers. We assume that there is a mass 1 of homogeneous advertisers. Advertisers wish for consumers to see their ads, as it may inform them about their product and translates into sales. As introduced previously, their valuation for an impression made on a consumer of a given platform depends on which service this platform is using to offer its ad space. An advertisers runs an advertising campaign on P_i for $i \in \{1, 2\}$ if it gets positive utility. Advertisers can multi-home. Denoting the mass of consumer on platforms i as n_i^C we have that:

- If P_i offers its ad-space through I , an advertiser runs an ad campaign on P_i if:

$$k \cdot n_i^C - p_i \geq 0$$

- If P_i offers its ad-space through E , an advertiser runs an ad campaign P_i if:

$$k(1 + \Delta) \cdot n_i^C - p_i \geq 0$$

Consumers. There is a mass 1 of single-homing consumers, uniformly distributed along an Hotelling (1929) line. Platforms are located at the extremes of the line. We assume that P_1 is located in 0 and that P_2 is located in 1. This allows us to account for consumers' different tastes for content. For instance, if we think of our platforms as news providers, some consumers may prefer to inform themselves by consuming content made available on YouTube and others may have a preference for content available on *The Guardian*. We introduce a differentiation parameter $t > 0$, which captures the level of differentiation between the platforms from the consumers' perspective. A consumer's cost for joining a platform located at a distance d on the Hotelling line from them is equal to $t \cdot d$.

Platforms provide consumers with some content, which brings them a intrinsic utility of joining their platform of $v > 0$. It is assumed high enough for the market to be covered.

As in Anderson and Coate (2005), we consider that consumers dislike ads. The higher the number of ads they are being displayed, the worse is their consumer experience. We introduce an ad-nuisance parameter $\gamma > 0$, that captures this negative network effect exerted by advertisers on consumers. The total ad-nuisance a consumer exposed to an ad-level $a \geq 0$ suffer from is equal to $\gamma \cdot a$.

Hence, the utility from joining platform P_i for $i \in \{1, 2\}$ for a consumer located at a distance d_i and being exposed to an ad-level a_i is $v - \gamma a_i - t d_i$.

Timing. We will consider two scenarios: (1) the incumbent has not yet acquired any downstream platform; (2) the incumbent has acquired one of the downstream platform. The timing will be slightly different in the two scenarios, as we outline below.

In the first stage, we endow the incumbent with a certain degree of commitment power, enabling it to commit to a commission rate α_I .

In the second stage, we assume that the entrant can observe the commission rate offered by the incumbent. With this information, the entrant can decide to enter the market by paying an entry cost e . Upon entering, the entrant will set its commission rate α_E in order to compete with the incumbent and induce platforms to adopt its *adtech* stack.

In the third stage, we assume that platforms observe the commission rates offered by both *adtech* stacks. In scenario (1), they decide which one to use going forward and simultaneously determine their advertising level a_i . In scenario (2), only the independent platform decide which *adtech* stack to adopt, as the newly acquired platform will use its own. Then, they simultaneously set their advertising level a_i . The merged entity maximizes joint-profits.

In the fourth stage, consumers observe the level of advertising on each platform. Considering their preferences and the potential inconvenience caused by ads, they make a decision regarding which platform they wish to use.

In the fifth and final stage, platforms simultaneously set the price of an advertising campaign p_i , taking into account the size of their user base and the level of indirect network effect they have on advertisers. Note that in scenario (2), the merged entity will maximize joint-profits. Following this, advertisers observe the advertising prices set by the platforms and make decisions about which platform(s) they wish to join, if any.

The equilibrium concept is sub-game perfect Nash equilibrium.

We can comment some assumptions of the model. First, one could question the commitment power given to the incumbent *adtech* stack. This commitment power can be attained through long-term contracts with downstream platforms, for instance. This assumption seems reasonable, as according to the French Competition Authority, publishers do not change their advertising technology provider on a regular basis⁸, and that commission rates are contractual. It also serves as a mean to provide the incumbent with additional power to deter potential entry. This stands in contrast to a situation where they would be unable to commit, which we discuss later in the paper, even though it does not seem like the most realistic timing.

Second, We assume that platforms do not incur any switching costs when transitioning to the entrant's *adtech* stack. However, we will discuss this possibility in Section 5.

Finally, we choose to assume that platforms decide on how much ad-space they want to offer before setting the price and before the advertisers' demand is realized. It appears to be quite reasonable, as it can be observed that some websites sometimes offer display advertising slots that they did not manage to sell, leaving an empty window on consumers' screens. Yet, we could also think about a different timing, where platforms set their advertising price, advertisers decide to buy it or not, and then the platform chooses an advertising level given the advertisers demand. The equilibrium would not be affected by this alternative timing.

3 Separated *adtech* stack incumbent

In this section, we examine the scenario in which the incumbent has not acquired any downstream display advertising platform. We can think of this as a world where a company like Google does not own a platform such as YouTube, which would enable it to directly reach consumers and display ads to them.

The situation is represented in Figure 2. As evident from this figure, platforms have direct access to consumers. However, in order to reach advertisers, they must choose

⁸See page 76 of decision no. 21-D-11, available at: [https://www.autoritedelaconurrence.fr/\[...\]](https://www.autoritedelaconurrence.fr/[...])

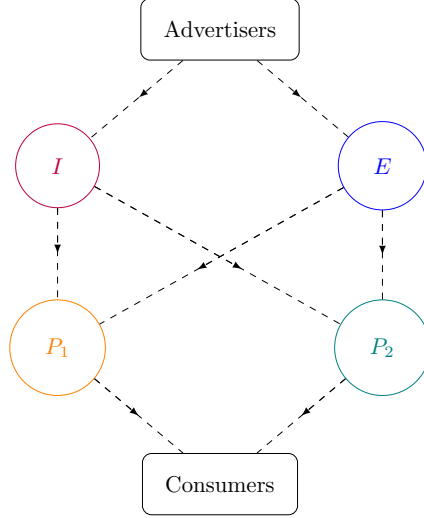


Figure 2: Separated *adtech* stack Incumbent

between the two *adtech* stacks. In this scenario, the incumbent lacks a direct way to reach consumers and must persuade the platforms to adopt its *adtech* stack.

As the game is solved backwards, let us start by examining decisions from the final stage, regarding advertisers.

Advertising price and advertisers' decision

As specified previously, advertisers' valuation of interactions with consumers on a given platform depends on which *adtech* stack that platform has adopted. Both advertisers and platforms observe the consumer demand. Consider an advertiser, it wants to run ad campaign on platform P_i if and only if it brings it positive utility.

Assume P_i is using the incumbent's service, it means that the value of an impression on P_i 's consumers for an advertiser is k . Consequently, the valuation of an ad campaign on P_i for an advertiser is $k \cdot n_i^C$, representing the number of impressions made times their value for advertisers. For an advertiser to wish to run an ad campaign, the latter value must exceed the advertising price. This condition can be expressed as follows: $k \cdot n_i^C - p_i \geq 0$.

Assume now that P_i is using the (more efficient) entrant's service. The value of an impression on P_i 's consumers for an advertiser is $k \cdot (1 + \Delta)$, which is larger than if it had adopted the incumbent's AdTech stack. This implies that the condition for an advertiser to wish to run an ad campaign on P_i can be expressed as follows: $k \cdot (1 + \Delta) \cdot n_i^C - p_i \geq 0$.

It is evident that the platforms will be able to charge higher prices for an ad campaign when utilizing the entrant's *adtech* stack. This is because it is more efficient - e.g. better targeting, etc. These efficiency gains, which enhance the value of an impression for advertisers, ultimately enable platforms to extract higher revenues from advertisers.

Now that we examined advertisers' decisions, we assume that the platforms anticipate it and simultaneously set their advertising prices accordingly. Given that advertisers are multi-homers, there is no competition for advertisers between platforms. The following lemma characterizes the equilibrium concerning advertisers' decisions and pricing.

Lemma 1 *There exists a unique equilibrium where:*

- *If platform P_i has adopted the incumbent's adtech stack, its advertising price is*

$$p_i = k \cdot n_i^C$$
- *If platform P_i has adopted the entrant's adtech stack, its advertising price is*

$$p_i = k \cdot (1 + \Delta) \cdot n_i^C$$

In equilibrium, all advertisers want to run an advertising campaign on both platforms and get all of their surplus extracted.

Proof. See Appendix 9.1. ■

In equilibrium, platforms have the ability to set an ad campaign price that captures the entirety of advertisers' surplus while still attracting all of them. This is because advertisers are homogeneous and multi-home. The entrant's enhanced efficiency, initially benefiting advertisers, ultimately translates into higher revenues for the platforms, allowing them to charge higher prices. This hints at the likelihood that this competitive advantage will favor the entrant when platforms decide which *adtech* stack to adopt.

Now, we can proceed to examine consumers' decisions regarding which platform they prefer to engage with.

Consumers' decision

As specified in Section 2, consumers are uniformly distributed along an *Hotelling* line, with the platforms positioned at the two extremes. Consumers observe the advertising intensity on both platforms and make their decision based on this observation and their preferences. They are indifferent regarding which *adtech* stack the platform they join has adopted, as it has no influence on their utility.

The following lemma characterizes the consumer demands in equilibrium.

Lemma 2 *In equilibrium, the Hotelling consumer demands are:*

$$n_i^C = \frac{1}{2} + \gamma \cdot \frac{(a_j - a_i)}{2t}$$

Proof. See Appendix 9.2. ■

Examining consumer demands, it becomes evident that the dimension of platform competition for consumer attention lies in the level of advertising. Displaying fewer ads

than their competitors can assist platforms in attracting higher demand. Due to the negative cross-group network externalities, representing the inconvenience consumers experience from advertising, ad levels play a role quite analogous to prices in more conventional settings.

Now that we have computed the consumer demands, we can examine the ad-level decision made by the platforms.

Platforms' ad-level and *adtech* stack decision

Platforms anticipate the impact of their ad-level decision on consumer demands. Additionally, they are aware that all advertisers are willing to run an ad campaign at the profit-maximizing price determined earlier. Consequently, this decision involves platforms setting a cap on the number of ads they will display in order to maximize profits. If a platform sets an ad level a_i (≤ 1), it will randomly select from the entire pool of advertisers those who will be authorized to purchase ad space. This involves finding a balance between selling more ad space for higher volumes and minimizing the inconvenience to consumers.

Platforms profits depend on which *adtech* stack they adopted. Consider platform P_i and assume it adopted the incumbent's *adtech* stack. It makes the following profit:

$$\Pi_i(a_i, a_j) = (1 - \alpha_I) \cdot a_i \cdot k \cdot \left(\frac{1}{2} + \gamma \cdot \frac{(a_j - a_i)}{2t} \right) \quad (2.1)$$

Assume now that it has adopted the entrant's *adtech* stack, it makes the following profit:

$$\Pi_i(a_i, a_j) = (1 - \alpha_E) \cdot a_i \cdot k \cdot (1 + \Delta) \cdot \left(\frac{1}{2} + \gamma \cdot \frac{(a_j - a_i)}{2t} \right) \quad (2.2)$$

Depending on its competitor's and its own *adtech* stack decision, a platform maximizes its profit by adjusting its ad level. The following lemma characterizes the ad level chosen by platforms in equilibrium:

Lemma 3 *In equilibrium, platforms, regardless of which adtech they have adopted, set the ad level*

$$a_i = \frac{t}{\gamma} \equiv a_b,$$

where a_b will denote the baseline competitive ad level from now on. With this ad level set, we observe that the equilibrium is symmetric, and $n_i^C = \frac{1}{2}$.

Proof. See Appendix 9.3. ■

Assumption 2 (Limited platform market power) *We assume that $t < \gamma$ to ensure that the market power of platforms in the market for consumer attention remains limited enough for them to exert competitive pressure on each other.*

By analyzing the equilibrium ad level a_b , we observe some intuitive comparative statics. This quantity increases with the differentiation parameter t , meaning that as the platforms' market power increases, they can display a greater number of ads to consumers. Conversely, as the ad nuisance parameter γ rises, the equilibrium ad level decreases, as ads become more bothersome for consumers.

We substitute equilibrium ad levels and consumer demand into (2.1) and (2.2), allowing us to express platform profits as a function of their *adtech* stack decision:

- If a platform has adopted the incumbent's *adtech* stack: $\Pi_i = (1 - \alpha_I) \cdot \pi_b$
- If a platform has adopted the entrant's *adtech* stack: $\Pi_i = (1 - \alpha_E) \cdot (1 + \Delta) \cdot \pi_b$

With $\pi_b = \frac{k}{2} \cdot a_b$, a notation introduced to represent the baseline competitive profit.

We are now able to examine platforms' *adtech* stack decision. As outlined in Section 2, platforms adopt the *adtech* stack that enables them to make the highest profit. Platforms are symmetric and will ultimately make the same *adtech* stack decision. To be specific, assuming that the entrant did enter, they adopt the entrant's *adtech* stack if and only if:

$$(1 - \alpha_E) \cdot \pi_b \cdot (1 + \Delta) \geq (1 - \alpha_I) \cdot \pi_b \quad (WC_{sep})$$

As anticipated when we analyzed the advertising price decision, the enhanced efficiency of the entrant effectively translates into a competitive advantage from the platforms' perspective. Indeed, it's worth noting that if both *adtech* stacks were to offer the same commission rate ($\alpha_I = \alpha_E$), the entrant would be the preferred choice since $(1 + \Delta) \geq 1$, resulting in higher platform profits.

Therefore, thanks to its more efficient technology, the entrant empowers platforms to charge higher advertising prices and enjoys a competitive advantage compared to the incumbent.

The entrant's winning condition (WC_{sep}) can be rewritten as

$$\alpha_E \leq 1 - \frac{(1 - \alpha_I)}{1 + \Delta},$$

and represented by the following Figure 3:

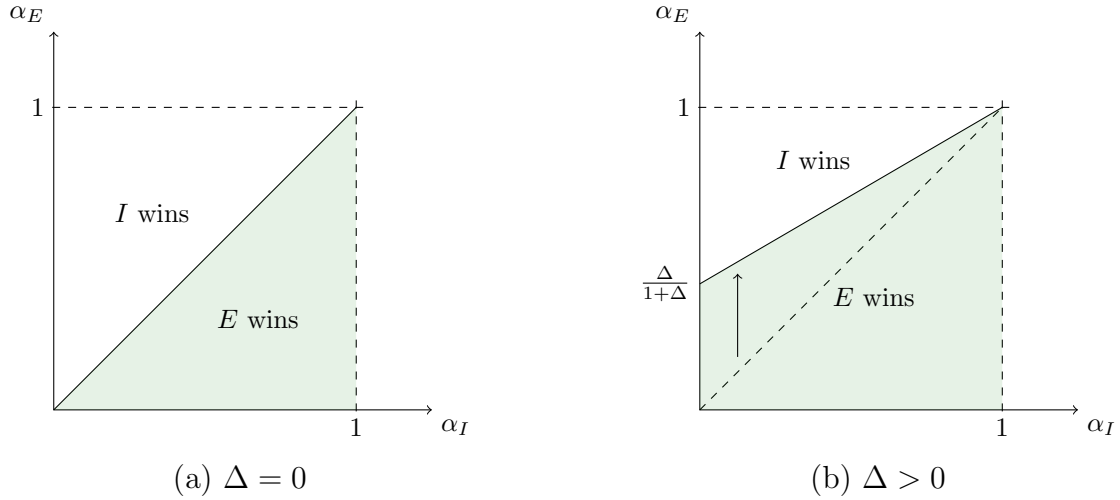


Figure 3: E 's winning condition on commission rates when I is separated

By looking at Figure 3(a), we see that absent enhanced efficiency for the entrant ($\Delta = 0$), and conditional on entrant's entry, the winner is the cheapest *adtech* stack. However, with superior technology ($\Delta > 0$), the entrant can charge a higher commission rate than the incumbent while still persuading platforms to adopt its *adtech* stack.

It is worth noting that if the entrant decides to enter and compete, it can secure a guaranteed victory in the market. Even if the incumbent sets a zero commission rate, the entrant would still capture the market with a positive commission rate $\alpha_E = \frac{\Delta}{1+\Delta}$.

Now that we have determined the platforms' AdTech stack choice conditional on entry and commission rates, we can proceed to analyze the decisions of the entrant.

Entrant's pricing and entry decision

Let us first assume that entry has occurred. Our objective is to examine the pricing decision of the entrant. While we know that the entrant can outperform the incumbent for all possible values of α_I by satisfying (WC_{sep}) , the question is whether it chooses to do so and, if it does, at what exact commission rate?

Lemma 4 *If entry has occurred, the entrant's profit-maximizing commission rate is:*

$$\alpha_E(\alpha_I) = 1 - \frac{(1 - \alpha_I)}{1 + \Delta} \quad (\geq \alpha_I)$$

This commission rate represents the highest possible rate that allows the entrant to displace the incumbent.

Proof. See Appendix 9.4 ■

The entrant sets the highest commission rate that allows it to secure victory. It is clear that it can still set a higher commission rate than the incumbent. If the entrant enters, the incumbent is not able to defeat it, even by setting a zero commission rate.

By setting its profit-maximizing commission rate, the entrant generates the following profit:

$$\begin{aligned}\Pi_E(\alpha_I) &= \alpha_E(\alpha_I) \cdot 2 \cdot (1 + \Delta) \cdot \pi_b - e \\ &= \left(1 - \frac{(1 - \alpha_I)}{1 + \Delta}\right) \cdot 2 \cdot (1 + \Delta) \cdot \pi_b - e\end{aligned}\tag{2.3}$$

Having calculated the entrant's profit if it were to enter, we can now examine its entry decision. If the entrant chooses not to enter, it makes zero profit; if it enters, it yields the profit expressed in (2.3). Therefore, it will decide to enter if the following condition is satisfied:

$$\left(1 - \frac{(1 - \alpha_I)}{1 + \Delta}\right) \cdot 2 \cdot (1 + \Delta) \cdot \pi_b - e \geq 0$$

This condition can be rewritten as:

$$\alpha_I \geq \frac{e}{2\pi_b} - \Delta$$

Hence, the entrant's ability to enter depends on the incumbent's commission rate. If the incumbent commits to a sufficiently high commission rate, entry will take place, and the entrant will ultimately capture the market, setting the commission rate described in Lemma 4. It becomes evident that by committing to a low commission rate, the incumbent can deter entry, causing it to be unprofitable for the entrant. Now, let us examine whether the incumbent has the incentive and/or is capable of doing so.

Incumbent's commission decision

The incumbent has to decide whether to deter entry or not. To deter entry, it must commit to a commission rate α_I such that:

$$\alpha_I < 1 - \left((1 + \Delta) - \frac{e}{2\pi_b}\right) \tag{DC_{sep}}$$

If the incumbent sets a commission rate that does not satisfy the entry deterrence condition (DC_{sep}), it will enable entry but ultimately be defeated by the entrant, resulting in zero profit.

Conversely, by setting a commission rate that satisfies (DC_{sep}), it deters entry, remains the sole player in the market, and charges platforms the commission rate α_I . In this case, its profit is given by $\alpha_I \cdot 2 \cdot \pi_b$.

It is clear that for any positive commission rate that enables the incumbent to deter entry, it would prefer to do so in order to generate positive profits. Furthermore, since its profit in the case of entry deterrence increases with α_I , it commits to the maximum commission rate that still deters entry.

The following figure and proposition characterize the equilibrium of the game:

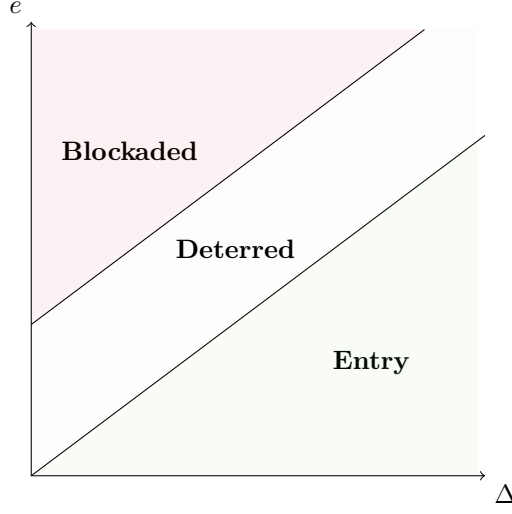


Figure 4: Entry with a separated *adtech* stack incumbent

Proposition 1 *The equilibrium can be described as follows:*

- For $e \leq 2 \cdot \pi_b \cdot \Delta$: **entry occurs**, and the entrant wins with $\alpha_E = \frac{\Delta}{1+\Delta}$
- For $2 \cdot \pi_b \cdot \Delta < e \leq 2 \cdot (1 + \Delta) \cdot \pi_b$: **entry is deterred**, and the incumbent remains the sole player in the market, with limit pricing α_I slightly below $\frac{e}{2\pi_b} - \Delta$
- For $e > 2 \cdot (1 + \Delta) \cdot \pi_b$: **entry is blockaded**, and the entrant poses no competitive threat to the incumbent, resulting in $\alpha_I = 1$

Proof. See Appendix 8.1. ■

For low entry costs relative to the gains from the entrant's enhanced efficiency, entry occurs, and the entrant wins the market. The level of advertising is equal to a_b , and the entrant's commission rate is $\alpha_E = \frac{\Delta}{1+\Delta}$. The entrant's profit is given by $\alpha_E \cdot 2 \cdot (1+\Delta) \cdot \pi_b - e$, and the profits of both platforms are given by $(1 - \alpha_E) \cdot (1 + \Delta) \cdot \pi_b$. Therefore, industry profit equals $2 \cdot (1 + \Delta) \cdot \pi_b - e$.

For intermediate entry costs relative to the gains from the entrant's enhanced efficiency, entry is deterred, and the incumbent manages to be the sole player in the market. The level of advertising is equal to a_b , and the incumbent charges platforms with its committed limit pricing commission rate $\alpha_I = \frac{e}{2\pi_b} - \Delta$. The incumbent's profit is given by $\alpha_I \cdot 2 \cdot \pi_b$, and the profits of both platforms are given by $(1 - \alpha_I) \cdot \pi_b$. Industry profit is thus equal to $2 \cdot \pi_b$.

For high entry costs relative to the gains from the entrant's enhance efficiency, entry is blockaded, as the entrant is not efficient enough to pose any threat to the incumbent. The level of advertising is once again set at a_b . Being the sole player and facing no relevant threat of entry, the incumbent charges the maximum commission rate $\alpha_I = 1$, leaving

the platforms with zero profits. The incumbent captures the entire industry profit given by $2 \cdot \pi_b$.

Welfare

For all areas of parameter described in Proposition 1, it can be interesting to compare the final outcome with the social optimum. We are basically wondering if the right *adtech* stack won.

Both advertisers and consumers are indifferent to which *adtech* stack platforms ultimately adopt. For advertisers, their surplus is captured anyway, and for consumers, whose consumer surplus depend on nuisance they suffer from advertising, it remains constant as the level of advertising does not depend on the winning *adtech* stack.

Then, our objective becomes to compare industry profits. When the entrant enters and wins, the industry profit is given by $(1 + \Delta) \cdot 2 \cdot \pi_b - e$, and when the incumbent wins, the industry profit is given by $2 \cdot \pi_b$. By comparing the two, we observe that it is only desirable for the entrant to enter when $e \leq 2 \cdot \Delta \cdot \pi_b$. This is exactly what happens in equilibrium, the outcome is thus socially optimal.

We have computed the equilibrium with a separated *adtech* stack incumbent, which is not integrated with any downstream display advertising platform. Our analysis has identified parameter regions where entry would occur, where entry would be deterred (along with the corresponding limit pricing), and where entry would be blockaded. We have also determined the level of advertising consumers would be exposed to in the absence of integration. In the following section, we will assume that the *adtech* stack incumbent acquires one of the two downstream platforms and compare the outcomes.

4 Integrated *adtech* stack incumbent

In this section, we will examine the scenario in which the incumbent has acquired a downstream display advertising platform. We will assume that the acquired platform is P_1 . This setting is intended to represent situations like the current state of the market, where a dominant *adtech* stack, such as Google, owns a significant downstream display advertising platform like YouTube. Through this acquisition, the incumbent gains direct access to consumer attention.

Figure 5 represents such situation. We denote the merged entity as $I - P_1$. As illustrated in the figure above, the advertising space of $I - P_1$ is now exclusively available through its own and operated *adtech* stack. Consequently, the only advertising space for which *adtech* stacks can compete for is P_2 's, the remaining independent platform's. This results in a reduction in the potential market size for the entrant.

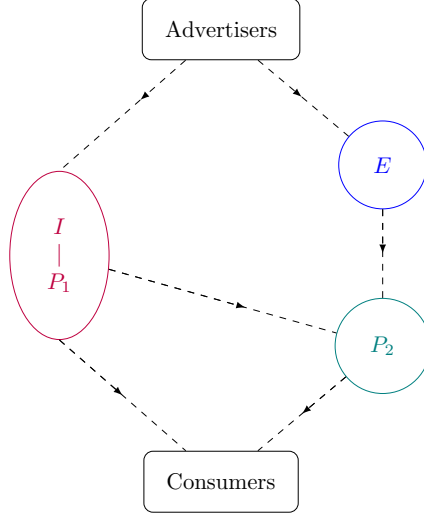


Figure 5: Integrated *adtech* stack Incumbent

$I - P_1$ now makes its decisions in order to maximize joint profit. The timing of the game is not really affected, the only change is that now, only P_2 must choose an *adtech* stack to offer its ad space to advertisers.

Let us now solve the game backwards.

Advertising price and advertisers' decision

The advertisers' decision remains unaffected by integration. Their willingness to pay for a platform's advertising space still depends on its user base and on which *adtech* stack it has adopted, but not on the structure downstream.

$I - P_1$ will use its own *adtech* stack, and thus, advertisers will want to run an advertising campaign if $k \cdot n_{I-P_1}^C - p_{I-P_1} \geq 0$.

Concerning P_2 , the advertiser demand depends, as in the separated case, on which *adtech* stack it has adopted. As outlined in Section 3, if it has adopted the incumbent's service, advertisers wish to run an ad campaign if $k \cdot n_2^C - p_2 \geq 0$. If it has adopted the entrant's service, advertisers wish to run an advertising campaign if $k \cdot (1 + \Delta) \cdot n_2^C - p_2 \geq 0$.

Platforms anticipate advertisers' decisions and simultaneously set the price of an advertising campaign. The following lemma characterizes the equilibrium advertising prices:

Lemma 5 *In equilibrium:*

- The merged entity $I - P_1$ charges advertisers a price $p_{I-P_1} = k \cdot n_{I-P_1}^C$ for an advertising campaign since it always uses its own service
- The independent platform P_2 charges:
 - $p_2 = k \cdot n_2^C$ if it uses the incumbent's *adtech* stack
 - $p_2 = k \cdot (1 + \Delta) \cdot n_2^C$ if it uses the entrant's *adtech* stack

In equilibrium, all advertisers want to run an advertising campaign on both platforms and get all of their surplus extracted.

Proof. The proof of this lemma follows the proof of Lemma 1 ■

At this stage, players' decisions remain unaffected by integration of the *adtech* stack incumbent with one of the downstream platform. This will not have an effect on advertising prices, and advertisers who run advertising campaigns will get all of their surplus extracted. Advertisers are thus rather indifferent to whether the incumbent is separated or integrated.

The newly acquired downstream display advertising platform is now limited to using the incumbent's service, its own, and loses the possibility to charge higher prices to advertisers by adopting the entrant's more efficient technology.

Consumers' decision

Consumers' decision is unaffected by the merger. One can easily prove, following the proof of Lemma 2, that consumer demands are as follows

$$n_i^C = \frac{1}{2} + \gamma \cdot \frac{(a_j - a_i)}{2t}$$

The expressions remain the same, but in equilibrium, demands may be different. The equilibrium outcomes, particularly the equilibrium advertising levels, may vary from those of Section 3.

Having determined consumer demands, let us now study platforms' decisions with respect to advertising level, and for those for which it is relevant, their *adtech* stack decision.

Platforms' ad-level and *adtech* stack decision

As already explained in Section 3, the platforms simultaneously set their advertising level and compete for consumer attention. In this stage, integration is going to have an effect, as competition will be affected depending on the independent platform's *adtech* stack decision.

Let us first consider the sub-game in which the independent platform, P_2 , has adopted the entrant's *adtech* stack. It can thus charge advertisers an advertising price equal to $k \cdot (1 + \Delta) \cdot n_2^C$. Platforms' profits write:

$$\begin{aligned}\Pi_{I-P_1} &= a_{I-P_1} \cdot k \cdot n_{I-P_1}^C \\ \Pi_{P_2} &= (1 - \alpha_E) \cdot a_2 \cdot k \cdot (1 + \Delta) \cdot n_2^C\end{aligned}$$

One can easily see that while the profit expressions for the merged entity have been affected by the merger in the sense that no commission rate appears anymore, the first-order conditions will not be altered. This implies that in the sub-game where P_2 adopted the entrant's *adtech* stack, advertising level decisions are not affected by integration, as described in the following lemma:

Lemma 6 *If the independent platform has adopted the entrant's adtech stack, the equilibrium advertising levels set by platforms are as follows:*

$$a_{I-P_1} = a_b = a_2$$

As a result, consumer demands are symmetric and equal to $\frac{1}{2}$.

Proof. As stated earlier, one can verify that first-order conditions are the same to those in the proof of Lemma 3. Hence, following this proof, we obtain the same equilibrium outcomes. ■

We can thus express equilibrium profits as a function of the commission rate charged by the entrant:

$$\begin{aligned}\Pi_{I-P_1} &= \pi_b \\ \Pi_{P_2} &= (1 - \alpha_E) \cdot (1 + \Delta) \cdot \pi_b\end{aligned}$$

It is interesting to note that, as a consequence of Lemma 6, we can conclude that if the entrant enters and wins, consumers are indifferent between a situation with a separated or an integrated incumbent. Let us now examine whether this still holds if P_2 adopts the incumbent's *adtech* stack.

Consider the sub-game in which the independent platform has adopted the incumbent's *adtech* stack. Consequently, it can charge advertisers an advertising price equal to $k \cdot n_2^C$ and must share a proportion α_{I-P_1} of its advertising revenues with its direct competitor. Platforms' profits are given by:

$$\begin{aligned}\Pi_{I-P_1} &= \overbrace{a_{I-P_1} \cdot k \cdot n_{I-P_1}^C}^{\text{Own revenues}} + \alpha_{I-P_1} \cdot \overbrace{a_2 \cdot k \cdot n_2^C}^{P_2\text{'s revenues}} \\ \Pi_{P_2} &= (1 - \alpha_{I-P_1}) \cdot a_2 \cdot k \cdot n_2^C\end{aligned}\tag{2.4}$$

In this scenario, it is clear that integration will indeed affect equilibrium advertising levels. The merged entity partially internalizes its negative externalities on the independent platform through its commission rate α_{I-P_1} . The following lemma characterizes those equilibrium advertising levels:

Lemma 7 *If the independent platform has adopted the entrant's adtech stack, the equilibrium advertising levels set by the platforms are as follows:*

$$a_{I-P_1} = \frac{3 + \alpha_{I-P_1}}{3 - \alpha_{I-P_1}} \cdot a_b \quad (\geq a_b)$$

$$a_2 = \frac{3}{3 - \alpha_{I-P_1}} \cdot a_b \quad (\geq a_b)$$

Consequently, consumer demands are as follows:

$$n_{I-P_1}^C = \frac{3 - 2 \cdot \alpha_{I-P_1}}{3 - \alpha_{I-P_1}} \cdot \frac{1}{2} \leq \frac{1}{2}$$

$$n_2^C = \frac{3}{3 - \alpha_{I-P_1}} \cdot \frac{1}{2} \geq \frac{1}{2}$$

Proof. See Appendix 9.5. ■

We update Assumption 2 to ensure that even in the scenario with an integrated incumbent, platforms market power is limited enough.

Assumption 3 (Limited platform market power) *We assume that $2t < \gamma$.*

Assumption 3 ensures that advertising levels have relevant values. We apply this more restrictive assumption to all settings for comparability.

As anticipated, in the scenario where the independent platform has adopted the incumbent's *adtech* stack, integration has indeed impacted the equilibrium. This results in consumers being exposed to more ads, which reduces their utility. Indeed, the merged entity now partially internalizes the impact of its decisions on the independent platform. If $I - P_1$ decreases its ad level, P_2 's demand and revenues will decrease and, ultimately, so will the revenues the merged entity is able to earn generate from its advertising technology provision business. This creates an opportunity cost, leading the merged entity to have lower incentives to display fewer ads. Additionally, the equilibrium is now asymmetric, and the total transport cost is no longer minimized. Consequently, when the incumbent is the winning *adtech* stack, integration is detrimental to consumers, as their surplus is lower compared to the separated incumbent case.

Platforms profits are also impacted, they write:

$$\Pi_{I-P_1} = \pi_b \cdot \frac{(3 - 2 \cdot \alpha_{I-P_1})(3 + \alpha_{I-P_1})}{(3 - \alpha_{I-P_1})^2} + \alpha_{I-P_1} \cdot \pi_b \cdot \left(\frac{3}{3 - \alpha_{I-P_1}} \right)^2$$

$$\Pi_2 = (1 - \alpha_{I-P_1}) \cdot \pi_b \cdot \underbrace{\left(\frac{3}{3 - \alpha_{I-P_1}} \right)^2}_{\geq 1}$$

Now that we determined platforms' equilibrium advertising levels depending on the independent platform's *adtech* stack decision, and computed the corresponding profits,

we examine the *adtech* stack adoption decision. Assuming entry occurred, P_2 adopts the entrant's *adtech* stack if and only if:

$$(1 - \alpha_E) \cdot \pi_b \cdot (1 + \Delta) \geq (1 - \alpha_{I-P_1}) \cdot \pi_b \cdot \underbrace{\left(\frac{3}{3 - \alpha_{I-P_1}} \right)}_{\geq 1}^2 \quad (WC_{int})$$

By comparing (WC_{sep}) and (WC_{int}), we can clearly see the effect of integration on *adtech* stack decision.

In the scenario with a separated incumbent, it was clear that if both *adtech* stack offered the same commission rate ($\alpha_E = \alpha_I$), the more efficient entrant would win and get platforms to adopt its service.

In the scenario with an integrated incumbent, the decision is not as straightforward. If both *adtech* stacks offer the same commission rate, a platform may still opt for the incumbent's service because it could allow the platform to display more ads to consumers and generate higher profits. This implies that the reduced competition for consumer attention, which the platform would experience by adopting the incumbent's service, may compensate for the entrant's enhanced efficiency.

Proposition 2 *Integration between the adtech stack incumbent and a downstream display advertising platform allows the incumbent to gain a competitive advantage through an anti-competitive process.*

Integration affect platforms' advertising level decision, and the incumbent can offer softened competition for consumer attention to the independent platform if it adopts its adtech stack.

This mechanism closely resembles the *collusive effect* of vertical mergers identified by Chen (2001). The author finds that a vertical merger involving an upstream supplier and a downstream producer can alter the pricing incentives of the downstream producer because it might become the supplier to its competitor. If the independent producer decides to be supplied by the integrated firm, competition in the final market is softened, which can, in turn, influence the choice of supplier.

In our paper, however, the *collusive effect* of integration is not realized through pricing but through advertising levels, which represent a means for platforms to manage indirect network effects between consumers and advertisers.

The entrant's winning condition (WC_{int}) can be rewritten as:

$$\alpha_E \leq 1 - \frac{1 - \alpha_{I-P_1}}{1 + \Delta} \cdot \left(\frac{3}{3 - \alpha_{I-P_1}} \right)^2 \quad (WC_{int})$$

It is apparent that due to the presence of the last term on the right-hand side of the condition, which exceeds 1, it becomes more challenging for the entrant to outperform an

integrated incumbent. This term captures the increased potential profit the independent platform could obtain by adopting the incumbent's *adtech* stack, thanks to the *collusive effect* of the merger. This is also evident on the following figure:

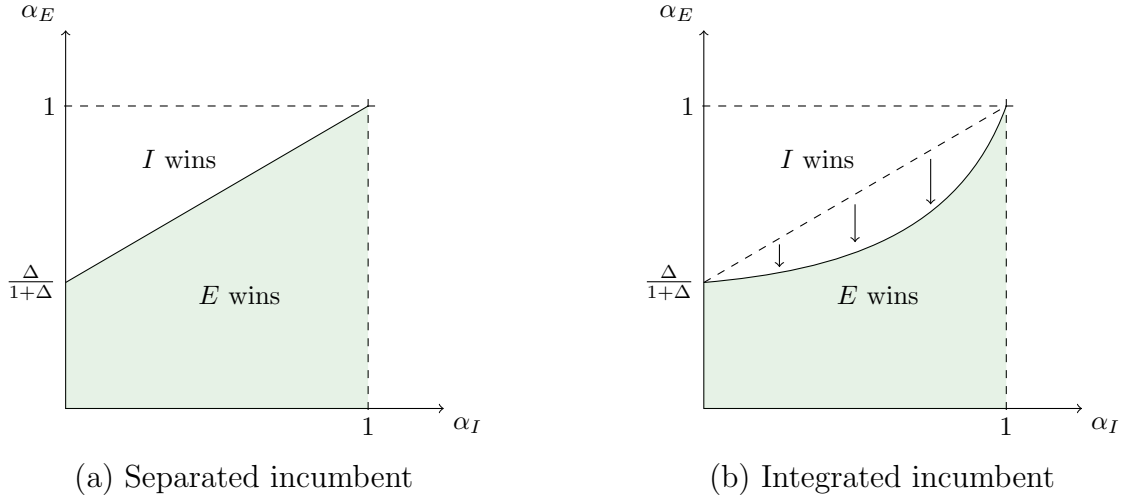


Figure 6: E 's winning condition on commission rates when I is separated vs. integrated

We can visually observe that integration, through its *collusive effect*, affects competition within the *adtech* stack. It is clear that the region where the entrant can outperform the incumbent diminishes in size.

Now that we quantified the effects of integration on the independent platform's *adtech* stack decision, we can examine how it translates it terms of entrant's pricing and entry.

Entrant's pricing and entry decision

Let us first assume that entry has occurred. Our objective is to examine the entrant's pricing decision. The entrant can get the independent platform to adopt its service by satisfying (WC_{int}) . The following lemma characterizes the commission rate it will set:

Lemma 8 *If entry has occurred, the entrant's profit-maximizing commission rate is:*

$$\alpha_E(\alpha_{I-P_1}) = 1 - \frac{1 - \alpha_{I-P_1}}{1 + \Delta} \cdot \left(\frac{3}{3 - \alpha_{I-P_1}} \right)^2$$

*This commission rate is the highest possible such that the independent platform adopts the entrant's *adtech* stack.*

Proof. See Appendix 9.6. ■

So, the entrant sets the highest commission rate that it can, and it is not able to charge a price as high as when facing a separated incumbent because of the softened competition the incumbent can offer to the independent platform if its service is adopted. The entrant

generates the following profit:

$$\begin{aligned}\Pi_E(\alpha_{I-P_1}) &= \alpha_E(\alpha_{I-P_1}) \cdot (1 + \Delta) \cdot \pi_b - e \\ &= \left(1 - \frac{1 - \alpha_{I-P_1}}{1 + \Delta} \cdot \left(\frac{3}{3 - \alpha_{I-P_1}}\right)^2\right) \cdot (1 + \Delta) \cdot \pi_b - e\end{aligned}\tag{2.5}$$

By comparing the profit the entrant makes when entering while facing a separated incumbent (2.3) and while facing an integrated incumbent (2.5), we can observe that two primary factors may make it more challenging for the entrant to successfully enter in the latter case.

First, the *collusive effect* of integration limits the ability for the entrant to charge sufficiently high commission rates to the independent platform while still getting it to adopt its service.

Second, the market size for the entrant is only half as large as it would be when facing a separated incumbent. Consequently, the size of the market it can compete for is not as substantial as it would be in the absence of integration, which diminishes the profitability of entry.

Knowing the entrant's profit, we can examine its entry decision. It enters if it makes a positive profit, so if:

$$\left(1 - \frac{1 - \alpha_{I-P_1}}{1 + \Delta} \cdot \left(\frac{3}{3 - \alpha_{I-P_1}}\right)^2\right) \cdot (1 + \Delta) \cdot \pi_b - e \geq 0$$

Which can be rewritten as:

$$\alpha_{I-P_1} \geq 1 - \left(\left(1 + \Delta\right) - \frac{e}{\pi_b}\right) \cdot \left(\frac{3 - \alpha_{I-P_1}}{3}\right)^2$$

Hence, the entrant's ability to enter depends once again on the incumbent's commission rate α_{I-P_1} . This implies that by setting a low enough commission rate, the incumbent can deter entry. Let us now examine whether the incumbent does so.

Incumbent's commission decision

The incumbent decides whether to deter entry or not. To deter entry, it must commit to a commission rate α_{I-P_1} such that:

$$\alpha_{I-P_1} < 1 - \underbrace{\left(\left(1 + \Delta\right) - \frac{e}{\pi_b}\right)}_{\leq (1+\Delta) - \frac{e}{2\pi_b}} \cdot \underbrace{\left(\frac{3 - \alpha_{I-P_1}}{3}\right)^2}_{\leq 1} \tag{DC}_{int}$$

When examining and comparing both entry deterrence conditions, (DC_{sep}) and (DC_{int}),

it becomes apparent that it is easier to satisfy for an integrated incumbent. Therefore, an integrated incumbent can more easily deter entry and exert less effort on its commitment. This is achievable because integration reduces the entrant’s market size and enables the incumbent to gain a ”competitive advantage” by offering softened downstream competition to the independent platform.

As in the scenario with a separated incumbent, the incumbent optimally commits to the maximum commission rate that deters entry, as long as this commission rate is positive. The following figure and proposition characterize the final equilibrium of the game with an integrated incumbent:

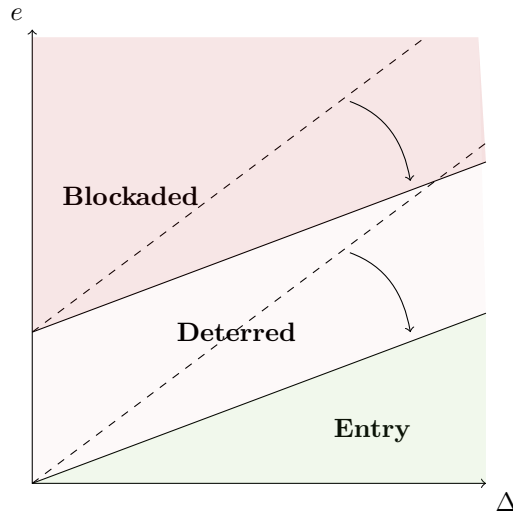


Figure 7: Entry with an integrated *adtech* stack incumbent

Proposition 3 *The equilibrium is as follows:*

- For $e \leq \Delta \cdot \pi_b$: **entry occurs**, and the entrant wins with $\alpha_E = \frac{\Delta}{1+\Delta}$
- For $\Delta \cdot \pi_b < e \leq (1 + \Delta) \cdot \pi_b$: **entry is deterred**, and the incumbent remains the sole player in the market, with limit pricing, but it is able to charge a higher commission rate than when it was separated
- For $e > (1 + \Delta) \cdot \pi_b$: **entry is blockedaded**, and the entrant poses no competitive threat to the incumbent, resulting in $\alpha_{I-P_1} = 1$

Proof. See Appendix 8.2. ■

For added clarity, a plot illustrating the commission rates for various entry cost values can be found in Appendix 10.1, along with a plot showing the advertising levels in Appendix 10.2.

By comparing the equilibria described in Proposition 1 and Proposition 3, we can draw several conclusions.

Firstly, the integration of an *adtech* stack incumbent with a downstream display advertising platform results in reduced entry. Although we identified two factors that could potentially lead to less entry, it is only the reduction in market size that actually induces a decrease in entry. By acquiring one of the two downstream platforms, the *adtech* stack incumbent can effectively exclude its newly acquired firm from the entrant's competitive scope. Consequently, the profitability of entry decreases, causing the entrant to abstain from entering the market across a broader range of parameters.

Secondly, integration results in higher advertising levels and, consequently, more nuisance for consumers. To be more specific, integration has no effect on consumers when entry takes place. However, consumers do experience increased nuisance due to integration when the merged entity emerges as the winner, as the *collusive effect* of the merger comes into play, leading the platforms to set higher advertising levels. Therefore, compared to the scenario with a separated incumbent, consumers endure greater ad-nuisance when entry does not occur, and this is more frequent as integration also discourages the entrant.

Lastly, integration also impacts the incumbent's ability to impose high commission rates. The previously mentioned *collusive effect* of integration enables the merged entity to charge higher commission rates while still effectively deterring entry. Ultimately, integration serves as a means for the incumbent to reduce the competitive pressure imposed by the entrant and it raises barriers to entry.

Welfare

In this section, we discuss briefly the welfare implications of the merger between the *adtech* stack incumbent and a downstream display advertising platform.

Firstly, let us discuss the impact of integration on consumer surplus. As discussed in the previous section, it increases advertising levels, thereby influencing the ad-nuisance experienced by consumers. However, we also need to consider the impact on the total transportation costs that consumers incur in our *Hotelling* setting.

If $e \leq \Delta \cdot \pi_b$, entry occurs with both a separated and an integrated incumbent. The entrant outperforms the incumbent, and platforms set advertising levels at a_b , which represents our baseline competitive advertising level. This leads to symmetric consumer demands and minimizes total transportation costs.

If $e > \Delta \cdot \pi_b$ however, entry does not occur with an integrated incumbent. With a separated incumbent, entry would occur but it would not affect consumers. No matter what, they would be exposed to the baseline level of advertising a_b with symmetric demands. However, with an integrated incumbent, the *collusive effect* of integration leads platforms to set higher levels of advertising, thereby increasing the ad-nuisance experienced by con-

sumers. Furthermore, as demands are now asymmetric (due to differing advertising levels between the merged entity and the independent platform), total transportation costs are no longer minimized and become higher than in the scenario with a separated incumbent. Consequently, consumer surplus is strictly lower with integration.

Hence, we can conclude that integration is generally detrimental to consumers.

Let us now examine the impact of integration on private agents. The merged entity consistently benefits from it if $\Delta \leq 1$, and the *adtech* stack incumbent and the downstream display advertising platform would engage in this profitable merger. If $\Delta > 1$, the merger is not profitable for $e \leq \Delta \cdot \pi_b$ and would not be agreed upon. However, it becomes profitable for $e > \Delta \cdot \pi_b$. When the merger is deemed profitable, the overall surplus of the firms involved increases with integration. This increase occurs because the incumbent can secure one of the two downstream platforms' ad space, as well as ensure that entry is reduced. Furthermore, when entry does not occur, it can display more ads and thus increase its profits.

From the perspective of the independent platform, there are conflicting effects. On the one hand, integration leads to reduced competitive pressure from the entrant for the *adtech* stack incumbent, enabling it to charge higher commission rates. On the other hand, the *collusive effect* allows the incumbent to display more ads due to the reduced competition for consumer attention. The overall impact of integration on the independent platform remains uncertain.

Overall, conducting additional analysis to ascertain the impact of integration on total welfare would be necessary. Nevertheless, the unequivocal result regarding consumer surplus already permits us to draw certain conclusions regarding what changes a regulator focused on maximizing consumer surplus would consider. It is evident that integration raises concerns for such regulator when $e > \Delta \cdot \pi_b$.

5 Robustness checks

In this section, we discuss some robustness checks we have conducted. Our results are robust to those changes in our model: (1) the addition of switching costs; (2) a change in timing.

Switching costs

In our model, we assumed that display advertising platforms did not have any switching costs associated with choosing the entrant's service. However, if we assume that in previous periods, they were using the incumbent's service, one could argue that they

would incur a switching cost $s > 0$ to transition to the entrant’s service. Switching to the entrant’s service could indeed be costly, as it may necessitate platforms to adapt their infrastructure to ensure compatibility with the new *adtech* stack’s APIs, for instance.

The introduction of such a cost would hinder the entrant’s ability to charge commission rates as high as $\frac{\Delta}{1+\Delta}$ when it enters. Consequently, this would reduce the profitability of entry and result in less entry. The reduction in entry would occur in similar proportions in both scenarios, whether there is a separated or an integrated incumbent. Therefore, introducing switching costs does not mitigate or intensify the impact of integration on entry; it merely makes entry less likely to occur to a similar extent in all settings.

Change in the timing

Up until this point, we have assumed that the incumbent has commitment power, enabling it to deter entry effectively. One could argue, however, that the incumbent might choose to revise its prices and directly compete with the entrant⁹.

In light of this, we have examined an alternative timing. In this revised timing, we have eliminated the initial stage where the incumbent commits. Instead, we now assume that the incumbent sets its commission rate after the entry decision. If entry did not occur, it can freely set its commission rate and it becomes the sole player in the market. If entry has taken place, *adtech* stacks simultaneously set their commission rates, engaging in competition *à la Bertrand*.

This change in timing does not significantly alter our results. The parameter regions where entry occurs remain the same. The only difference is the absence of entry deterrence since there is no commitment in this new timing. In those parameter regions where entry would have been deterred through limit pricing, entry now does not occur, and the incumbent can charge the maximum commission rate of 1. The *collusive effect* of integration persists; therefore our findings regarding consumer surplus remain applicable with this alternative timing and are, in fact, exacerbated.

6 Extension: Capping advertising levels

In this paper, we find a similar *collusive effect* of integration to Chen (2001)’s. We show that similar mechanisms to those identified in their paper might be at play in the online display advertising industry.

The main takeaway from our paper is that an *adtech* stack incumbent, through integration with a downstream display advertising platform, can more effectively deter the entry of a more efficient entrant. This is accomplished through two mechanisms. First, it

⁹Note that as already discussed in the presentation of the timing of the game in Section 2, our first assumption is more realistic according to the French Competition Authority’s investigations (see decision no. 21-D-11).

can secure the ad space of the newly acquired platform, preventing its competitor from being able to compete for it. Second, it can also provide softened competition to the unintegrated platform, compensating for its relative lack of efficiency compared to the entrant. Consequently, it can gain a competitive advantage through a mechanism that is detrimental to consumers, who experience increased ad nuisance.

Hence, a regulator focused on maximizing consumer surplus would be inclined to prevent such a situation from arising and should aim to prohibit such a merger. However, if we consider that the *adtech* stack and the display advertising platform are already integrated, as in the case of YouTube and Google, a regulator may contemplate various remedies.

It could consider a very drastic but also costly and complex structural remedy: separation. The U.S. Justice Department has already explored this option in its lawsuit against Google for monopolizing digital advertising technologies, where it requests Google’s divestiture of certain segments of its *adtech* stack¹⁰.

A behavioral remedy, aimed at protecting consumers, could involve imposing an advertising level cap, drawing inspiration from European Union legislation that restricts the duration of commercial breaks on TV¹¹. For instance, platforms could be prohibited from displaying more ads than they would at the baseline competitive advertising level – in our paper, a_b . By doing so, the regulator would prevent the *collusive effect* of integration from materializing. Consumer surplus would remain unchanged, whether the incumbent *adtech* stack is integrated or not with a downstream platform.

While setting an advertising-level cap at the competitive level ($\bar{a} = a_b$) seems intuitive, in practice, it is unlikely that a regulator can precisely estimate this quantity. More likely, it will pseudo-arbitrarily set a cap such as no more than 20% of the watch time or no more than 20% of the user screen surface is occupied by advertising while scrolling, for example. In this section, we will consider a scenario where a regulator imposes a symmetric ad-level cap on both platforms, which can be either above or below the competitive ad-level.

Symmetric advertising level regulation. Let us introduce a quantity $\delta \in [0, 1]$ which captures how far from the competitive ad-level is the cap imposed by the regulator.¹² The ad-level regulation could be either *strict* or *lenient*. A *strict* regulation means that the ad-level cap \bar{a} is below the competitive level a_b , such that $a_b > \bar{a} = a_b(1 - \delta)$. A *lenient* regulation means that the ad-level cap is above the competitive level, such that $a_b < \bar{a} = a_b(1 + \delta)$. Those two types of ad-level regulation would have different effects, as detailed in Proposition 4.

¹⁰See the press release available at <https://www.justice.gov/opa/pr/justice-department-sues-google-monopolizing-digital-advertising-technologies>

¹¹See Article 18(2) of the directive 97/36/EC available at <https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:31997L0036>

¹²We acknowledge that we model the imprecision in the regulator’s decision in a very simple way.

Proposition 4

If the regulation is **strict** ($\bar{a} < a_b$), the ad-levels chosen by both platforms are equal to the ad-level cap \bar{a} . Consumer exposure to ads decreases and the realization of the collusive effect of integration is prevented. However, such regulation also makes entry less profitable and, ultimately, less likely.

If the regulation is **lenient** ($\bar{a} > a_b$), it can have no effect. Yet, for some values of parameter, the regulation limits the increased consumer exposure to ads and the collusive effect due to integration – though to a lesser extent than with a strict regulation. Entry is not affected, but the competitive pressure from potential entry is enhanced. The closer the ad-level cap is to the competitive ad-level a_b , the more efficient the lenient regulation becomes.

Proof. See Appendix 8.3 ■

Our analysis provides interesting insights into the effects of a restriction on online display advertising levels in the spirit of the European Union’s legislation on TV. A *lenient* regulation, setting a cap not so restrictive, could have no effect. However, as this cap approaches the competitive ad-level, it could increase the competitive pressure on the integrated *adtech* stack incumbent by limiting the collusive effect of integration while also decreasing consumer exposure to ads. Entry would be unaffected.

A *strict* regulation, setting a very restrictive cap, will always affect the outcome of the game. It will drastically reduce consumer exposure to ads and completely eliminate the collusive effect of integration. However, the resulting decrease in profitability for new entrants must be considered, as it could lead to ambiguous effects of the regulation depending on the regulator’s objectives.

Stimulating efficient entry. Both regulations will naturally reduce equilibrium advertising levels and limit pricing, leading to a fairer advertising revenues sharing between the independent platform and the integrated *adtech* stack. However, we show that ad-level restrictions cannot stimulate entry, though it might be desirable. We know that in the absence of regulation, efficient entry does not occur for $e \in [\Delta \cdot \pi_b, 2 \cdot \Delta \cdot \pi_b]$, due to the reduction in market size resulting from integration. A *strict* advertising restriction can exacerbate this situation. To address this issue, the ad-level cap should be complemented with a regulation that allows the entrant to compete for ad-space on the integrated display advertising platform.

Asymmetric regulation. So far, we have argued that imposing a restriction on advertising levels is credible, as it aligns with existing laws in the European Union. However, it is evident that monitoring a limited number of TV channels is far simpler than monitoring the multitude of display advertising platforms on the internet. Focusing enforcement of

the regulation solely on integrated display advertising platforms such as YouTube could reduce the regulation’s cost of implementation. Our analysis can provide insights into the effects of introducing asymmetry in ad-level capping.

An asymmetric *lenient* regulation will be as efficient as the symmetric one. The regulation could achieve its intended effects while being less costly to implement.

With a *strict* regulation, asymmetry will allow the unregulated independent platform to increase its advertising level. This would result in higher consumer exposure to advertising but could also encourage more market entry compared to a symmetric regulation. These two effects need to be balanced, considering the reduced implementation costs as well.

To summarize, imposing a restriction on advertising levels in the online display advertising market, similar to European regulations on TV commercial breaks, appears reasonable. It could mitigate the negative effects of integration between an *adtech* stack firm and a display advertising platform. Ideally, the regulator aims to constrain platforms to achieve competitive advertising levels. We acknowledge potential imperfections in implementing such regulations and discuss their effects.

A *strict* regulation would significantly benefit consumers but could hinder efficient entry. A *lenient* regulation would moderately benefit consumers without negatively impacting entry. Asymmetric regulation can be as efficient as a symmetric one, while being less costly to implement, but it might also fail to reduce consumer exposure to ads as much as a symmetric regulation.

However, as our approach may not sufficiently stimulate efficient entry, it could be complemented with other regulatory measures aimed at mitigating the market size reduction effects of integration.

7 Conclusion

In this paper, we have developed a stylized model to study competition for consumer attention between display advertising platforms, as well as competition and entry upstream in the *adtech* stack. Our objective was to examine the impact of integration between an *adtech* stack incumbent and a downstream display advertising platform on these two vertically related markets.

Our findings suggest that such integration can effectively raise barriers to entry in two main ways. First, the acquisition of a display advertising platform by the *adtech* stack incumbent prevents new entrants from competing for the newly acquired ad space. Second, the collusive effect of integration allows the merged entity to reduce competitive pressure from new entrants while creating a softer competitive environment in the market for consumer attention. Consequently, vertical integration in the online display adver-

tising industry is unilaterally detrimental to consumers. Various competition authorities have rightfully expressed concerns about Google’s position within the *adtech* stack, but we argue that its position downstream with YouTube should also be a primary concern.

Separation could be a solution to address these issues, but it would likely be difficult to enforce. We argue that in this situation, the social planner is not tool-less. In more conventional settings, the anti-competitive effects of integration are often achieved through pricing mechanisms, and we know that prices can be challenging to cap and regulate, especially for end-consumers. However, the mechanisms at play in our model rely on advertising levels, which might be more reasonably regulated. The regulator could impose restrictions on the quantity of advertising that display advertising platforms show to their consumers. The European Union already enforces similar regulations on commercial breaks on TV. For example, we could limit the proportion of consumers’ watch time that advertising represents on YouTube. Considering potential imperfections in such regulation, we provide insights into their possible effects. Overall, such regulation could prove useful in addressing some of the issues related to integration. More specifically, a lenient restriction would slightly protect consumers while ensuring that there is no negative impact on entry, whereas a strict restriction would offer considerable consumer protection but would negatively impact potential entrants.

While this study has interesting policy implications, there is ample room for future research. For instance, we could explore the possibility of platforms developing their own advertising technology. Other intriguing aspects to study could involve expanding the set of actions available to consumers. For example, consumers can install ad-blockers to protect themselves from ad nuisance. In 2024, YouTube has engaged in a fierce battle against such technology, indicating that consumers and firms might strategically react to the use of ad-blockers. Both of these aspects could potentially alter our results and could be examined in future research.

8 Appendix A

8.1 Proof of Proposition 1

Proof. Assume that $e \leq 2 \cdot \pi_b \cdot \Delta$ we can observe that $\frac{e}{2 \cdot \pi_b} - \Delta \leq 0$. By revisiting the entry deterrence condition (DC_{sep}), we can deduce that to deter entry, the incumbent would need to commit to α_I such that:

$$\alpha_I < \frac{e}{2 \cdot \pi_b} - \Delta \leq 0$$

This would allow the incumbent to become the sole player in the market, secure victory, but ultimately result in negative profit. Hence, for these parameter values, the incumbent does not deter entry and prefers to make zero profit. The Bertrand competition process leads to $\alpha_I = 0$, the entrant enters, and it wins the market by setting $\alpha_E = \frac{\Delta}{1+\Delta}$.

Assume now that $2 \cdot \pi_b \cdot \Delta < e \leq 2 \cdot (1 + \Delta) \cdot \pi_b$. Assume that the entrant commits to an α_I just below $\frac{e}{2 \cdot \pi_b} - \Delta > 0$. By doing so, it successfully deters entry. This is an equilibrium because there is no profitable deviation. Any increase in its commission rate would result in entry, leading to zero profit as the incumbent would be defeated by the entrant. Any decrease in the commission rate would not increase demand but would only reduce profit. Hence, this commitment represents an equilibrium. Hence, it is an equilibrium. Committing to any $\alpha_I \geq \frac{e}{2 \cdot \pi_b}$ would result in zero profit, and the incumbent would have an incentive to lower its commission rate until entry is deterred. Committing to any positive α_I below the equilibrium would imply that the incumbent has a profitable deviation in increasing its commission rate. Therefore, for this range of parameters, the equilibrium commitment is $\alpha_I = \frac{e}{2 \cdot \pi_b} - \Delta - \epsilon$, with an infinitesimal $\epsilon > 0$. In this case, entry is deterred, and the incumbent adopts limit pricing.

Assume that $e > 2 \cdot (1 + \Delta) \cdot \pi_b$. This corresponds to a parameter range where the entry cost for the entrant is higher than the maximum profit it could ever make. Consequently, the entrant poses no threat to the incumbent. In equilibrium, the incumbent can commit to $\alpha_I = 1$ since entry is deterred regardless of its choice, and it can extract all the surplus from platforms. There are no profitable deviation. There are no other equilibrium candidates. Any α_I below this would not be an equilibrium because it would be profitable to increase it, and any α_I above this would result in no participation from the platform, yielding zero profit. Therefore, for this range of parameters, entry is blockaded, and $\alpha_I = 1$ in equilibrium. ■

8.2 Proof of Proposition 3

Proof. Let us first show that the incumbent indeed set the maximum commission rate that allows it to deter entry.

If α_{I-P_1} is such that (DC_{int}) is not satisfied *i.e.* the commission rate is too high, entry occur and the incumbent is outperformed. The merged entity profit is equal to π_b .

If α_{I-P_1} is such that (DC_{int}) is satisfied *i.e.* the commission rate is low enough, entry is deterred and the incumbent is the sole player on the market. The merged entity profit is given by $\pi_b \cdot \frac{(3-2\alpha_{I-P_1})(3+\alpha_{I-P_1})}{(3-\alpha_{I-P_1})^2} + \alpha_{I-P_1} \cdot \pi_b \cdot \left(\frac{3}{3-\alpha_{I-P_1}}\right)^2$. One can easily verify that the left term of this profit is in itself already higher than π_b for $\alpha_{I-P_1} \in [0, 1]$.

Hence, it is evident that committing to any positive commission rate that allows the incumbent to deter entry would yield more profit for the incumbent. Moreover, the profit obtained by deterring entry is increasing in the commission rate, so the incumbent would maximize its profit by committing to the maximum commission rate that satisfy (DC_{int}) .

Let us introduce α^* such that:

$$\alpha^* = 1 - \left((1 + \Delta) - \frac{e}{\pi_b} \right) \cdot \left(\frac{3 - \alpha^*}{3} \right)^2$$

The incumbent would then commit to $\alpha_{I-P_1} = \alpha^* - \epsilon$ with $\epsilon > 0$.

We now want to find for which regions of parameters entry: occurs, is deterred, is blockaded. We will examine one way of doing so. Let us rearrange the entry deterrence condition, which can be written as follows:

$$\Pi_E(\alpha_{I-P_1}) = \left(1 - \frac{1 - \alpha_{I-P_1}}{1 + \Delta} \cdot \left(\frac{3}{3 - \alpha_{I-P_1}} \right)^2 \right) \cdot (1 + \Delta) \cdot \pi_b - e < 0$$

In other words, the merged entity must ensure that the entrant would make negative profit upon entering the market. It can be demonstrated that $\frac{\partial \Pi_E}{\partial \alpha_{I-P_1}} > 0$ for $\alpha_{I-P_1} \in [0, 1]$. This means that the entrant's profit upon entering the market strictly increases as the incumbent's commission rate rises. As the incumbent's commission rate increases, the profit gained by the independent platform from adopting the incumbent's *adtech* stack decreases, due to the intensive margin effect outweighing the extensive margin effect. Consequently, the entrant can more easily outperform the incumbent when the latter increases its commission rate.

Hence, we know two interesting things: the incumbent wants to ensure that the entrant's profit is negative upon entering, and these profits are strictly increasing in α_{I-P_1} . We will consider three scenarios (*I*), (*II*) and (*III*), described in the following figure:

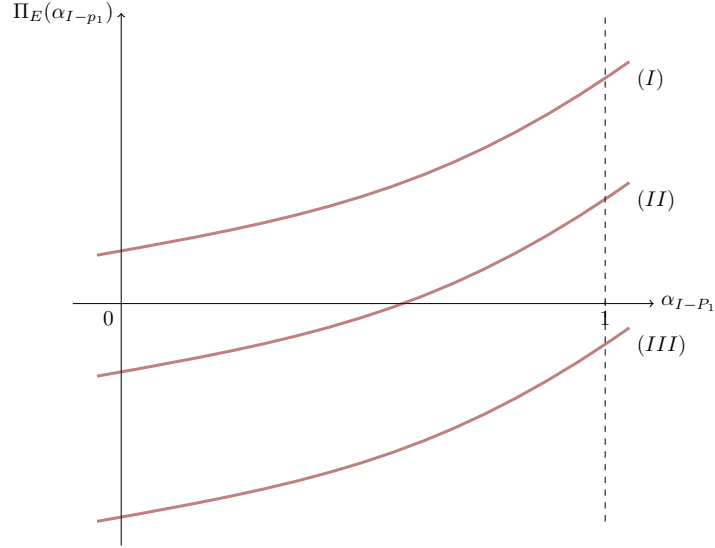


Figure 8: Representation of scenarios (I), (II) and (III).

In scenario (I), we see that there is no α_{I-P_1} such that the entrant would make zero or negative profit by entering. This corresponds to a scenario where entry would occur, as the incumbent is unable to avoid it. As we showed that the entrant's profit was increasing in the incumbent's commission rate, we know that this scenario would occur if $\Pi_E(0) \geq 0$ *i.e.* $\Delta \cdot \pi_b \geq e$.

In scenario (III), we see that for all possible values of α_{I-P_1} , the entrant would make negative profit upon entering. Hence, the incumbent can commit to a commission rate of 1, and the entrant would still not be able to profitably enter. Entry is blockaded. This scenario occurs if $\Pi_E(1) < 0$ *i.e.* $e > (1 + \Delta)\pi_b$.

In scenario (II), we see that there exist an $\alpha^* \in [0, 1]$, previously introduced, such that $\Pi(\alpha^*) = 0$. In such cases, the incumbent commits to a commission rate just below α^* , deterring entry with limit pricing and maximizing its profit. This scenario occurs if:

$$\begin{aligned} \Pi_E(0) < 0 \\ \& \Pi_E(1) \geq 0 \end{aligned} \Leftrightarrow \Delta \cdot \pi_b < e \leq (1 + \Delta) \cdot \pi_b$$

One can also verify that the commission rate the incumbent commits to under this limit pricing is higher than in the scenario with a separated incumbent as:

$$\alpha^* = 1 - \left((1 + \Delta) - \frac{e}{\pi_b} \right) \cdot \left(\frac{3 - \alpha^*}{3} \right)^2 \geq 1 - \left((1 + \Delta) - \frac{e}{\pi_b} \right) \geq \frac{e}{2 \cdot \pi_b} - \Delta$$

■

8.3 Proof of Proposition 4

Proof.

Strict regulation. Let us first study the impact of a strict regulation, with an ad-level cap imposed to platforms such that $\bar{a} < a_b$. We introduce a parameter $\delta \in]0, 1]$ such that $\bar{a} = a_b(1 - \delta)$. We can indeed see that with this definition, the cap is below the competitive ad-level, and that the larger is δ , the stricter the regulation.

We consider that the incumbent *adtech* stack is integrated with one of the downstream display advertising platform, as in Section 4. We will study the impact of introducing the regulation in this setting.

It will affect the advertising levels decisions. If the independent platform previously adopted the entrant's *adtech* stack, the merged entity and the independent platform's best responses write:

$$\begin{cases} a_{I-P_1}(a_2) = \frac{t}{2\gamma} + \frac{a_2}{2} \\ a_2(a_{I-P_1}) = \frac{t}{2\gamma} + \frac{a_{I-P_1}}{2} \end{cases}$$

We know that in the absence of regulation, the equilibrium ad-levels are a_b , but this is above the cap. From the best responses, constrained by the cap, we can show that in equilibrium, both platforms set their ad-level at the cap \bar{a} .

If the independent platform decided to use the incumbent's service, the best responses are not the same:

$$\begin{cases} a_{I-P_1}(a_2) = \frac{t}{2\gamma} + (1 + \alpha_{I-P_1}) \cdot \frac{a_2}{2} \\ a_2(a_{I-P_1}) = \frac{t}{2\gamma} + \frac{a_{I-P_1}}{2} \end{cases}$$

With the merged entity partially internalizing its externalities on the independent platform. In equilibrium, the advertising levels should be:

$$\begin{cases} a_{I-P_1} = \frac{3 + \alpha_{I-P_1}}{3 - \alpha_{I-P_1}} \cdot a_b \geq a_b > \bar{a} \\ a_2 = \frac{3}{3 - \alpha_{I-P_1}} \cdot a_b \geq a_b > \bar{a} \end{cases}$$

We can show that, in equilibrium, because of the constraint imposed by the regulator, both platforms end up setting their ad-level equal to the cap \bar{a} .

A first conclusion can be drawn, that is that this regulation will reduce the level of advertising the consumers will be exposed to.

We also can easily get the intuition that the capping allowed to constraint platforms responses and prevent the realization of the collusive effect of integration. But, to confirm this intuition, let us have a look at independent platform's *adtech* stack decision.

Conditional on entry, it chooses to use the entrant's service if and only if:

$$(1 - \alpha_E) \cdot \frac{k}{2} \cdot \bar{a} \cdot (1 + \Delta) \geq (1 - \alpha_{I-P_1}) \cdot \frac{k}{2} \cdot \bar{a}$$

$$\Leftrightarrow \alpha_E \leq 1 - \frac{1 - \alpha_{I-P_1}}{1 + \Delta}$$

Hence, the condition for the entrant to win is the same as in the separated case. The regulation eliminated the possibility for the merged entity to gain a competitive advantage by offering softened competition for consumer attention.

Now, we want to study the effects of the regulation on entry. We saw above that it helps the entrant keep its competitive advantage, but that it also reduces the quantity of advertising that platforms can sell, ultimately reducing the profitability of entry, as evident from below:

$$\begin{aligned} \Pi_E &= \alpha_E \cdot \frac{k}{2} \cdot (1 + \Delta) \cdot \bar{a} - e \\ &= \alpha_E \cdot \pi_b \cdot (1 - \delta) \cdot (1 + \Delta) - e \end{aligned}$$

Similarly to what we did earlier, we can find the deterrence condition:

$$\alpha_{I-P_1} < 1 - \left((1 + \Delta) - \frac{e}{\pi_b \cdot (1 - \delta)} \right)$$

One can see that the market size reduction resulting from integration remains but that the collusive effect of integration does not play a role anymore. However, the profitability of entry decreases leading to unclear effect on limit pricing to achieve entry deterrence.

From this and in the spirit of the proof of Proposition 1 and Proposition 3, we can show that entry occurs for $e \leq \Delta \cdot \pi_b \cdot (1 - \delta)$. There is less entry as a result of reduced profitability of entry. Entry is deterred for $e \in [\Delta \cdot \pi_b \cdot (1 - \delta), 2 \cdot \Delta \cdot \pi_b \cdot (1 - \delta)]$, with unclear effect on the limit pricing value. Entry is blockaded for $e \geq (1 + \Delta) \cdot \pi_b \cdot (1 - \delta)$.

So, we showed that a *strict* regulation 1) effectively protect consumers from excessive exposure to advertising, 2) eliminate the collusive effect of integration, but 3) results in less entry as a consequence of reduced profitability of entry.

Lenient regulation. Here, we study the impact of a *lenient* regulation on advertising level, with a cap imposed on platforms such that $\bar{a} > a_b$. Using the same parameter to measure the degree of leniency of the regulation as above, we assume that the cap writes $\bar{a} = a_b(1 + \delta)$.¹³

First, assume that the independent platform adopted the entrant's *adtech* stack. Ab-

¹³Note that if δ was to be larger than 1, the regulation would not have any sort of effect as the maximum ad-level that can be set absent regulation is $2 \cdot a_b$.

sent regulation, the equilibrium ad-levels are equal to $a_b < \bar{a}$, hence, the equilibrium is unaffected. Second, assume that the independent platform adopted the merged entity's service. Absent regulation, the equilibrium is:

$$\begin{cases} a_{I-P_1} = \frac{3+\alpha_{I-P_1}}{3-\alpha_{I-P_1}} \cdot a_b \\ a_2 = \frac{3}{3-\alpha_{I-P_1}} \cdot a_b \end{cases}$$

We can show that if $\alpha_{I-P_1} \leq \frac{3\delta}{1+\delta}$, platforms' decisions are unconstrained by the regulation. However, if $\alpha_I > \frac{3\delta}{1+\delta}$, by using the best responses, we can show that in equilibrium, $a_{I-P_1} = \bar{a}$ and $a_2 = a_b(1 + \frac{\delta}{2}) = \frac{a_b + \bar{a}}{2} < \bar{a}$. So, for relatively high values of the commission rate, the regulation effectively caps the merged entity's ad-level, leading the independent platform to set its advertising rate accordingly, both at lower levels than they would have absent regulation.

Now, let us study at which condition does the independent platform adopt the entrant's service.

1) If $\alpha_{I-P_1} \leq \frac{3\delta}{2+\delta}$:

$$\alpha_E \leq 1 - \frac{1 - \alpha_{I-P_1}}{1 + \Delta} \cdot \left(\frac{3}{3 - \alpha_{I-P_1}} \right)^2 \quad (WC_{int})$$

2) If $\alpha_{I-P_1} > \frac{3\delta}{2+\delta}$:

$$\begin{aligned} (1 - \alpha_E) \cdot \pi_b \cdot (1 + \Delta) &\geq (1 - \alpha_{I-P_1}) \cdot \pi_b \cdot \left(1 + \frac{\delta}{2} \right)^2 \\ \Leftrightarrow \alpha_E &\leq 1 - \frac{1 - \alpha_{I-P_1}}{1 + \Delta} \cdot \left(1 + \frac{\delta}{2} \right)^2 \end{aligned}$$

With $1 - \frac{1 - \alpha_{I-P_1}}{1 + \Delta} \cdot \left(1 + \frac{\delta}{2} \right)^2 > 1 - \frac{1 - \alpha_{I-P_1}}{1 + \Delta} \cdot \left(\frac{3}{3 - \alpha_{I-P_1}} \right)^2$ for $\alpha_{I-P_1} > \frac{3\delta}{2+\delta}$ which implies that the second condition is less restrictive than it would have been absent regulation.

From this, we can already get the intuition that the regulation can have no effect, but can also help limit the collusive effect of integration.

We can, taking into account the entrant's decision, provide the entry deterrence condition that the merged entity must verify to effectively prevent entry:

If $\alpha_{I-P_1} \leq \frac{3\delta}{2+\delta}$, entry is deterred if:

$$\alpha_{I-P_1} < 1 - \left((1 + \Delta) - \frac{e}{\pi_b} \right) \cdot \left(\frac{3 - \alpha_{I-P_1}}{3} \right)^2$$

If $\alpha_{I-P_1} > \frac{3\delta}{2+\delta}$, entry is deterred if:

$$\alpha_{I-P_1} < 1 - \left((1 + \Delta) - \frac{e}{\pi_b} \right) \cdot \frac{1}{\left(1 + \frac{\delta}{2}\right)^2}$$

$$\left(< 1 - \left((1 + \Delta) - \frac{e}{\pi_b} \right) \cdot \left(\frac{3 - \alpha_{I-P_1}}{3} \right)^2 \right)$$

Following the idea of the proof of Propositions 1 and 3, we can show that:

- For $e \leq \Delta \cdot \pi_b$, entry **occurs** and regulation does not affect the eq.
- For $e \in]\Delta \cdot \pi_b, (1 + \Delta) \cdot \pi_b]$, entry is **deterred** and:
 - if $e \leq (1 + \Delta) \cdot \pi_b - \left(1 + \frac{\delta}{2}\right)^2 \cdot \left(1 - \frac{3\delta}{2+\delta}\right) \cdot \pi_b$: the regulation does not affect the eq.
 - if not, regulation limits collusive effect of integration, consumer exposure to ads and limit pricing
- For $e > (1 + \Delta) \cdot \pi_b$ entry is **blocked** but regulation limits collusive effect and consumers' exposure to advertising

We can note that, in terms of *lenient* regulation efficiency, the lower the δ , the better.

■

9 Appendix B

9.1 Proof of Lemma 1

Proof. Consider a platform P_i . Assuming that it has adopted the incumbent's *adtech* stack, it faces the following advertiser demand:

$$\begin{cases} 1 & \text{if } p_i \leq k \cdot n_i^C \\ 0 & \text{if } p_i > k \cdot n_i^C \end{cases}$$

$p_i = k \cdot n_i^C$ is an equilibrium as there are no profitable deviations. Increasing the advertising price would result in a complete loss of demand for the platform. Conversely, decreasing it would fail to attract additional demand while generating reduced revenue per advertiser. Therefore, it is an equilibrium. It is unique since no other candidate is relevant. Any price higher than this would result in zero profit, and for any positive price below $k \cdot n_i^C$, increasing the price would constitute a profitable deviation, leading to increased profits without a reduction in demand.

Assume that P_i has adopted the entrant's *adtech* stack. The only change is in the enhanced advertisers' value of an impression, which impacts demand. The proof for this

scenario follows a very similar structure to the one above, and it becomes evident that $p_i = k \cdot (1 + \Delta) \cdot n_i^C$ is the unique equilibrium. ■

9.2 Proof of Lemma 2

Proof. Consider a consumer located at $x \in [0, 1]$. They derive utility $v - \gamma \cdot a_1 - t \cdot x$ from joining 1, and utility $v - \gamma \cdot a_2 - t \cdot (1 - x)$ from joining 2. As is common with *Hotelling* models of differentiation, we seek to find the indifferent consumer to compute demands.

The indifferent consumer is located at \tilde{x} , such that:

$$\begin{aligned} v - \gamma \cdot a_1 - t \cdot \tilde{x} &= v - \gamma \cdot a_2 - t \cdot (1 - \tilde{x}) \\ \Leftrightarrow \tilde{x} &= \frac{1}{2} + \gamma \cdot \frac{(a_2 - a_1)}{2t} \end{aligned}$$

Since the market is covered, we can compute consumer demands. We have that $n_1^C = \tilde{x}$ and $n_2^C = 1 - \tilde{x}$, hence:

$$n_i^C = \frac{1}{2} + \gamma \cdot \frac{(a_j - a_i)}{2t}, \text{ for } i \in \{1, 2\} \text{ and } j \neq i$$

■

9.3 Proof of Lemma 3

Proof. Consider a platform P_i . If it has adopted the incumbent's *adtech* stack, its profit is characterized by (2.1), and if it has adopted the entrant's, its profit is characterized by (2.2). In both cases, the second-order condition is satisfied, confirming that the profit functions are concave.

Therefore, we can apply the first-order condition, which results in $a_i(a_j) = \frac{t}{2\gamma} + \frac{a_j}{2}$, and this expression does not depend on the *adtech* stack decision. By intersecting the best responses, we find that in equilibrium, ad levels are symmetric, with $a_i = \frac{t}{\gamma}$ for $i \in \{1, 2\}$. ■

9.4 Proof of Lemma 4

Proof. Assuming entry has occurred, if the entrant sets any commission rate $\alpha_E > 1 - \frac{(1-\alpha_I)}{1+\Delta}$, it results in a profit of $-e$.

However, by setting any commission rate below $1 - \frac{(1-\alpha_I)}{1+\Delta}$, the entrant achieves a profit of $\alpha_E \cdot 2 \cdot (1 + \Delta) \cdot \pi_b - e \geq -e$.

Therefore, the entrant always aims to satisfy (WC_{sep}) and win the market.

Furthermore, it's evident that in the latter case, the profit increases with α_E . This implies that the entrant is willing to set the maximum commission rate that still allows it to outperform the incumbent, namely $\alpha_E = 1 - \frac{(1-\alpha_I)}{1+\Delta}$. ■

9.5 Proof of Lemma 7

Proof. Platforms aim to maximize their profits by adjusting their advertising levels. Their profits are expressed in (2.4), and one can easily verify that both profit functions are concave in platforms' advertising level. Solving for the first-order conditions, we get platforms best responses:

$$\begin{aligned} & \begin{cases} n_{I-P_1}^C - \frac{\gamma}{2t} a_{I-P_1} + \alpha_{I-P_1} \left(a_2 \cdot \frac{\partial n_2^C}{\partial a_{I-P_1}} \right) = 0 \\ n_2^C - \frac{\gamma}{2t} a_2 = 0 \end{cases} \\ \Leftrightarrow & \begin{cases} a_{I-P_1}(a_2) = \frac{t}{2\gamma} + (1 + \alpha_{I-P_1}) \frac{a_2}{2} \\ a_2(a_{I-P_1}) = \frac{t}{2\gamma} + \frac{a_{I-P_1}}{2} \end{cases} \end{aligned}$$

Finally, intersecting best responses, we get advertising levels described in Lemma 7. ■

9.6 Proof of Lemma 8

Proof. This proof follows the proof of Lemma 4. Assuming entry has occurred, if the entrant sets any commission rate $\alpha_E \geq 1 - \frac{1-\alpha_{I-P_1}}{1+\Delta} \cdot \left(\frac{3}{3-\alpha_{I-P_1}} \right)^2$, its profit equals $-e$ because the independent platform does not adopt its *adtech* stack.

By setting any commission rate below $1 - \frac{1-\alpha_{I-P_1}}{1+\Delta} \cdot \left(\frac{3}{3-\alpha_{I-P_1}} \right)^2$, the entrant achieves a profit of $\alpha_E \cdot (1 + \Delta) \cdot \pi_b - e$. Therefore, it is evident that it will set α_E such that (WC_{int}) is satisfied.

Finally, in equilibrium, it will set $\alpha_E = 1 - \frac{1-\alpha_{I-P_1}}{1+\Delta} \cdot \left(\frac{3}{3-\alpha_{I-P_1}} \right)^2$ since its profit increase in α_E . ■

10 Appendix C

10.1 Commission rates plot

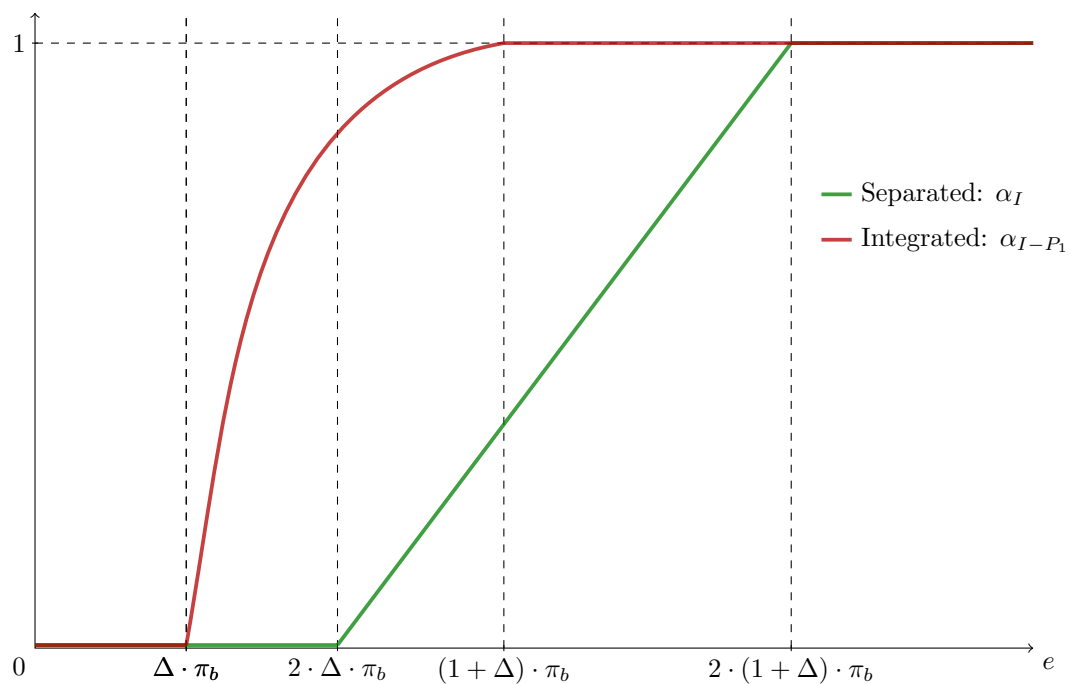


Figure 9: Comparison of the incumbent's commission rates: Separated vs. Integrated

10.2 Advertising levels plot

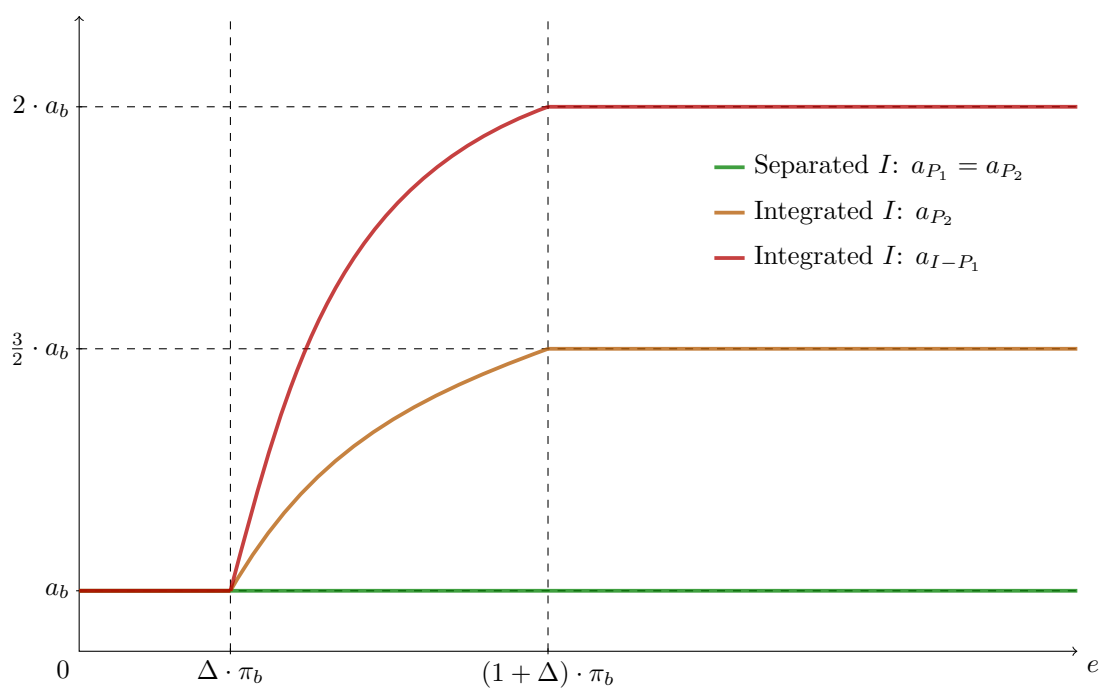


Figure 10: Comparison of advertising levels: Separated vs. Integrated

Chapter 3

Platform Information Provision : Evidence from an Online Auction Platform

1 Introduction

Digital platforms have drastically reduced the search costs of product discovery (Goldfarb and Tucker, 2019). This has made the market for niche products a possibility (Anderson, 2004; Brynjolfsson, Hu and Smith, 2006). However, by nature, buyers and sellers know little about the value of these niche products which are seldom traded and lack consumer feedback (Clemons, Gao and Hitt, 2006; Hu, Zhang and Pavlou, 2009). A unique product can hardly have received reviews from hundreds or thousands of consumers. The absence of information can potentially make the market collapse, to the detriment of buyers, sellers, and the digital platform (Hann and Terwiesch, 2003; Belleflamme and Peitz, 2018; Armstrong and Zhou, 2022; Tadelis, 2023). Indeed, buyers may fear a “winner’s curse” (Kagel and Levin, 1986) and be unwilling to buy a good without knowing its market or resale value.

This paper studies a potential solution to this problem put in place by Catawiki, a digital auction platform for “special, hard-to-find objects”.¹ This platform hired over 240 “experts” to curate goods and provide an assessment of their value in the form of minimum and maximum price estimates. In doing so, it follows the approach of traditional auction rooms where auctioneers can provide an estimation for a listed item (e.g, *commissaires-priseurs* from auction house in Paris, Hôtel Drouot). These estimates rely on the platform’s database recording the history of past sales and the experts’ knowledge (Malika, 2023; Fang et al., 2024). Such information provision has the potential to increase consumer surplus and platform profits (Jullien and Pavan, 2019; Armstrong and Zhou,

¹See <https://archive.is/wip/4utbB> for Catawiki’s self-description.

2022; Piolatto and Schuett, 2022; Lefez, 2022) by helping consumers better understand their willingness to pay, sellers their reservation value, and by improving the matching of the former to the latter through targeted ads and optimized search rankings (de Cornière and De Nijs, 2016; Janssen et al., 2023).

In doing so, the platform takes on a hybrid role as a matchmaker but also as an advisor to the market participants. These roles can potentially come in conflict with each other as highlighted by the recent literature on self-preferencing behavior by digital platforms, in particular in the context of private labels of e-commerce platforms.² This behavior has been sufficiently troublesome to merit a policy response in the form of the Digital Markets Act in the European Union (Waldfogel, 2024; Pape and Rossi, 2024). While less is known concerning how self-preferencing may affect information provision (Kirpalani and Philippon, 2020; Li, Tian and Zheng, 2021; Magnani and Navarra, 2023; Navarra et al., 2023), in particular from an empirical point of view, one may conjecture that the platform will have the incentive to over-estimate the value of goods to increase sales and commissions on the platform. This fear is particularly salient when there is no government oversight (Jin and Kato, 2006) and when buyers are unsophisticated. The latter risk being easily influenced by the online design (“dark patterns”) of the platform (Ghose, Ipeiroitis and Li, 2012, 2014; Akerlof and Shiller, 2015; Nosko and Tadelis, 2015; Fradkin et al., 2015; Chen and Yao, 2017; De los Santos and Koulayev, 2017; Anderson et al., 2020; Holtz et al., 2020; Hansen et al., 2021; Hagiu, Teh and Wright, 2022*b*; Hunold, Laitenberger and Thébaudin, 2022). Knowing this, users may distrust the information provided by the platform (Luca, 2017). This is plausible given the empirical evidence indicating that users distrust recommendations from sellers or platforms (Ba and Pavlou, 2002; Filieri and McLeay, 2014; Mudambi and Schuff, 2010; Benlian, Titah and Hess, 2012) as well as deceit arising more generally online (for example, one can think of fake reviews made by competing firms (Mayzlin, Dover and Chevalier, 2014; Luca and Zervas, 2016)). If users decide to completely ignore the estimates provided by the platform’s experts, the platform’s efforts will be nullified.

This raises the following questions which we address in this paper. Do users follow the platform’s experts’ estimates in their bidding strategy or are they ignored? If so, to what degree is this the case and are these estimates set in such a way as to maximise the platform’s profits? We show that the experts’ estimates are systematically above the realized expected final price. Nonetheless, we show that they influence consumer behavior and lead to higher prices and more sales on the platform. This suggests that agents trust, to some degree, the expert’s estimates as long as they are not extra-ordinarily high (and they rarely are). Why is this the case? We explore the economic mechanisms at play on

²See (Anderson and Bedre-Defolie, 2021; Lee and Musolff, 2021; Zenny, 2022; Hunold, Laitenberger and Thébaudin, 2022; Reimers and Waldfogel, 2023; Hagiu, Teh and Wright, 2022*b*, 2023; Etro, 2023; Waldfogel, 2024; Long and Amaldoss, 2024; Wang and Qiu, 2024).

sellers and buyers. We show that, surprisingly, sellers lower the probability of setting a reserve price following a high expert estimate. The good is also made more prominent on the platform, leading to the product attracting more bids. Keeping the the number of bids fixed, we show that the final price still rises, reflecting an increase in buyers' willingness to pay. We conclude that platform information can be provided in a way which is relied upon by the platform's users.

We use web-harvested data with rich information for over 57,000 objects listed on Catawiki during November 2023. We exploit the unique features of the platform to construct our identification strategy. In particular, we condition on the minimum expert estimate as a proxy for the fundamental value of a good, and focus our attention on the degree to which the maximum expert estimate differs from the minimum. As additional evidence, we leverage quasi-random variation in the experts' daily propensity to set high estimates in the form of instrumental variables. We consistently find that final bidden prices rise when the ratio of maximum to minimum estimates increases. We identify an upper limit to this behavior, which is seldom reached in practice. We assess the robustness of our estimates using alternative specifications as well as placebo tests, before focusing our attention on the economic mechanisms at play.

Our findings contribute to two broad literature. First, it builds upon the body of research investigating self-preferencing in digital markets through recommender systems. Many researchers have shown that consumers are very eager to follow recommendations made to them (Ghose, Ipeirotis and Li, 2012, 2014; Chen and Yao, 2017; De los Santos and Koulayev, 2017; Anderson et al., 2020; Holtz et al., 2020; Hansen et al., 2021). Moreover, these recommendations often have the interest of the platform in mind when they are designed (Hałaburda and Yehezkel, 2016; Hunold, Kesler and Laitenberger, 2020*b*; Aguiar and Waldfogel, 2021; Nagaraj and Ranganathan, 2022; Bourreau and Gaudin, 2022*b*). This can lead to low quality recommendations being made in practice (Fradkin et al., 2015; Horton and Golden, 2015; Zervas, Proserpio and Byers, 2021). Of particular relevance is Foroughifar and Mehta (2024) who study the adoption of algorithmic pricing advice by AirBnB hosts ("smart pricing"). They show using a structural model that prior beliefs regarding "smart pricing" lead some of the users who could benefit the most from it to also avoid using it. In contrast, the pricing advice we study is non-algorithmic and is also available to buyers. In our context, there is not already an abundance of data available.

Second, our study adds to the literature that studies auction design, and specifically auction platforms. Auction platforms have been studied from an econometric identification point of view in Marra (2021) who studies a change in fees in an online auction website focusing on vintage wine called BidforWine (which also has a lower and upper recommended price estimate). The auction theory literature acknowledges the importance of information acquisition in auction contexts. Milgrom and Weber (1982) show that providing potential buyers with information about object quality can raise expected

prices, and that the auction format affects the availability of information. Varma (2002) also emphasizes that the nature of information available to bidders is greatly influenced by the auction format, which in turn affects revenue. The incentives for bidders to acquire information are also impacted. While an extensive literature examines the impact of auction formats on information acquisition, most studies focus on static (or sealed-bid) auctions. Matthews (1977) studies information acquisition in first-price auction formats, and Persico (2000) and Bobkova (2024) compare first-price and second-price auction formats. However, online auction platforms like eBay typically use dynamic open auction formats. Unfortunately, experiments show that there is no equivalence between second-price auctions and ascending-price auctions (Kagel et al., 1987; Kagel and Levin, 1993). Yet, Compte and Jehiel (2007) show that dynamic formats, adopted by auction platforms, are likely to stimulate information acquisition and yield higher revenues than static ones. Even with the appropriate auction design, auction platforms should still seek to provide buyers with additional information, as it improves trade nonetheless (Levin, 2001). It is therefore critical for auction platforms to make information less costly for buyers to acquire, or even provide it directly, to help them assess their willingness to pay. An extensive empirical literature examines the impact of design choices on information provision and in turn, auction outcomes. Generally, reputation systems are effective in enabling sellers to capitalize on their reputation, either by allowing them to receive higher bids (McDonald and Slawson Jr, 2002; Livingston, 2005; Resnick et al., 2006) or by increasing sales volumes (Cabral and Hortacsu, 2010). However, for reputation systems to benefit higher-quality sellers, they must be designed appropriately (Cai et al., 2014; Klein, Lambertz and Stahl, 2013). Furthermore, the information available to users of online auction platforms can be biased, yet still influence their behavior (Nosko and Tadelis, 2015). Unfortunately, certain types of information can be misused; for instance, buyers may be overly optimistic when dealing with dishonest sellers (Jin and Kato, 2006), or market participants may be discriminated against based on irrelevant information (Doleac and Stein, 2013). This article emphasizes the importance of information provision on auction platforms and demonstrates that these platforms can adopt a more hybrid role by providing useful information to users, such as value estimates.

The remainder of the paper is organized as follows. Section 2 outlines the empirical context and data. Section 3 presents our empirical strategy. Section 4 shows our main results, while Section 5 discusses the economic mechanisms underlying these results. Finally, in Section 6 we provide concluding remarks.

2 Research Setting

2.1 Industry and Platform Context

Our analysis focuses on Catawiki, one of the leading digital platforms in Europe specializing in the auction of collectible items. Founded in 2008, it lists more than 75,000 objects each week. This relatively small number reflects the platform’s focus on selling ‘special objects,’ which range from inexpensive items, such as collectible stamps, to very expensive ones, like collectible cars. Catawiki can be considered as a blend between eBay and traditional (in-person) auction rooms³. Similar to eBay, it allows buyers from around the world to bid on items. However, it also incorporates a level of curation akin to that of an auction room. The platform employs over 240 in-house experts who are responsible for selecting which objects will be listed from the 12,000 daily submissions it receives. This vetting process enables Catawiki to maintain a certain level of quality control over the items offered on its website. Additionally, the experts can provide value estimates for objects, offering potential buyers a suggested price range. According to Catawiki, this expert evaluation aims to predict the likely final bid value of the items listed on their marketplace⁴. Figure 1 provides an example of the minimum and maximum estimated values given to potential buyers. Our analysis will focus on the effects of these expert estimates on consumer and seller behavior.

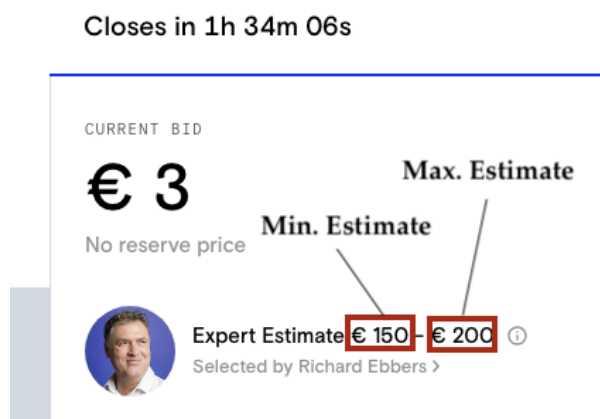


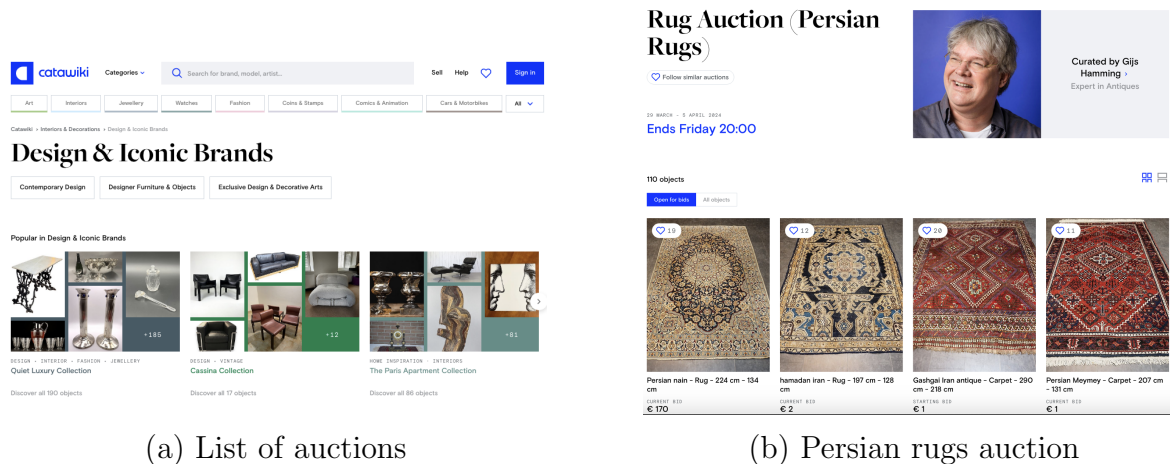
Figure 1: Expert Estimates

The platform organizes product listings into specific groups called “auctions”. Each auction typically focuses on a particular theme, type of object, historical period, or other distinguishing characteristics. For example, Figure 2(a) illustrates auctions within the “Design & Iconic Brands” category. Listings are organized into specific auctions, similar to the arrangement shown in Figure 2(b) which shows an auction for a collection of Persian rugs. Each auction is curated by an expert (e.g, Gijs Hamming or Richard Ebbers) who

³See this page for its self-description: [Catawiki - How is Catawiki different from other sales platforms](#)

⁴This statement can be found in Appendix 7.1

selects objects from relevant submissions. The bidding process for all items within a single auction opens and closes simultaneously.



(a) List of auctions

(b) Persian rugs auction

Figure 2: Illustrating the listings' organization

There are several specific features and details about the platform that are important to understand. To gain a better understanding of how Catawiki operates, consider the life cycle of an object submission. First, a seller submits an object to the platform. An expert then inspects the submission and determines whether the object should be listed and included in an auction. If so, the expert may provide its estimates⁵. If an expert estimate is provided, the seller has the option to set a reserve price, if not, they are not allowed to do so. Finally, buyers bid on the object in an “English” auction, a dynamic, ascending-price format. The highest bidder wins if there is no reserve price; if a reserve price is set, the highest bidder wins only if their bid exceeds this reserve price.

The estimation and reserve price features are critical aspects of the platform. Expert estimates provide buyers with valuable information regarding an object’s potential value but can also influence demand. The reserve price is another crucial element. The platform strongly advises sellers to refrain from setting a reserve price unless they are particularly risk-averse⁶. They argue that listings without a reserve price generally perform better, likely due to the dynamics of the bidding process. However, it is important to note that the platform itself may contribute to this outcome, as it allows users to filter listings specifically for those without a reserve price. Additionally, entire auctions are sometimes promoted as “No reserve price” auctions. The platform has a clear interest in promoting listings without reserve prices because this strategy ensures that they will generate revenue as long as at least one bid is placed. Catawiki charges a €3 + 9% fee on the buyer’s side and a 12.5% fee on the seller’s side. In terms of fees, Catawiki charges more than eBay, which charges a 10% fee on the seller’s side, but generally less

⁵It is important to note that for an estimation to be provided, the minimum value must exceed 150 euros and the maximum value must exceed 200 euros.

⁶See: [Catawiki - The Psychology Behind Selling Without a Reserve Price](#)

than traditional auction houses, positioning itself once again as a middle ground between these two models.

To summarize, Catawiki offers item curation akin to traditional auction houses and provides similar services through its in-house experts and their estimates. However, its online platform allows Catawiki to access a wider audience, thereby contributing to the broader democratization of auctions and second-hand purchases. Providing expert estimates at such a large scale raises the question of the quality of these estimates, as reflected by the numerous complaints which can be found on online user forums.⁷

2.2 Product Level Data

Using web scrapping techniques, we collect extensive data about a sample of objects listed on Catawiki's website. We compiled listing-level data with bid-level data to build a detailed cross-sectional dataset of objects listed from November 3rd 2023 to December 5th 2023. Information about the listings was collected once the auctions ended.

We filtered our data to only keep objects that received an expert estimate as we wish to analyze the impact of this information on buyers. This reduces our sample size from 116,327 observations to 62,829, as 54% of the objects were estimated. As we intend to use seller fixed-effects, we removed observations listed by a seller that supplied only one object. We applied minimal additional filtering to the data⁸, resulting in a very diverse and broad dataset of 57,201 observations. Table 7 presents a summary of our sample in Appendix 7.2.1. Despite covering only 1 month, our dataset contains a substantial number of observations. We have over 57,000 object listings, offered by more than 5,400 different sellers and featured in 1,681 different auctions, which gather on average 65 objects each⁹. Additionally, since Catawiki claims to have just over 240 experts, a vast majority of them is involved in our dataset, with 233 experts represented. Moreover, we have objects and auctions in every main category available on the platform (See Table 8 in Appendix 7.2.2). There is an important diversity in objects listed on Catawiki and present in our dataset, ranging from classic cars to stamps.

Several variables are at our disposal. For each object listed, we know the final bid or final price. Moreover, we know what were the minimum and the maximum value estimates attributed by the expert. This allows us to build a ratio between the maximum and the minimum estimates, which captures how the maximum estimate differs from the

⁷For example, one may consult this Reddit thread (<https://archive.is/wip/XG8Hn>) indicating concerns over the quality of the estimates and the incentives of the platform to manipulate demand through overinflated estimates.

⁸We removed 3 observations because of absurd estimation values and imposed a threshold such that the maximum estimate value is limited to 15 times the minimum estimate value. Moreover, as our identification strategy relies on using instrumental variables (see Section 3.3), we remove 6 observations for which we were not able to build the desired variables.

⁹This average number of objects per auction includes non estimated items.

minimum estimate. We also build a ratio between the final price and the minimum (resp. maximum) estimate, which captures how well an object performed relative to experts minimum (resp. maximum) prediction. Additionally, we know whether an estimated object had a reserve price or not. We also have measures of the object’s “popularity”, including the number of bids and the number of bidders, which we constructed from the bidding history. Finally, we have gathered some information about the prominence given to objects. An object is considered to have been promoted if it was featured on the cover images of its auction. Additionally, we have the rank of the object within its auction, which is determined by an expert and not by an algorithm¹⁰. Table 1 provides descriptive statistics at the object listing level.

Statistic	N	Mean	St. Dev.	Min	Median	Max
Final Price (€)	57,201	589.61	3,068.78	0	175	415,000
is Sold	57,201	0.43	0.49	0	0	1
Min. Estimate (€)	57,201	1,632.63	7,089.04	150	500	722,500
Max. Estimate (€)	57,201	1,904.70	7,958.84	200	600	795,000
Max./Min. Estimate Ratio	57,201	1.25	0.22	1.05	1.20	14.89
Price/Min. Estimate Ratio	57,201	0.43	0.33	0.00	0.40	8.72
Price/Max. Estimate Ratio	57,201	0.35	0.26	0.00	0.32	7.14
has Reserve Price	57,201	0.77	0.42	0	1	1
# of Bids	57,201	11.28	10.43	0	8	78
# of Bidders	57,201	5.04	4.02	0	4	46
is Promoted	57,201	0.08	0.27	0	0	1
Auction Rank	57,201	39.45	31.61	1	32	257

Note: Each observation used to construct this table corresponds to a unique object listing that received an expert’s estimates.

Table 1: Descriptive statistics for object listings

These summary statistics provide us with some insights into our data. First, let us look at the final price. It is evident that there is a strong long-tail effect. For instance, the mean price is substantially higher than the median, and we observe some extreme values, with the maximum final price reaching €415,000. More than half of the objects have a closing bid lower than a hundred and seventy-five euros, indicating that the majority of the objects are not of extremely high value.

The expert estimates follow a similar pattern. They are also right-skewed. On average, maximum estimates are 25% larger than minimum estimates, suggesting estimation window sizes to be, intuitively speaking, informative and precise. The ratios of price to minimum and maximum expert estimates indicate that expert estimates are over-inflated. Indeed, products have on average a final bidden price 66% and 74% lower than, respectively, the minimum and maximum expert estimates.¹¹ This indicates that

¹⁰See: [Catawiki - How Are Objects Ranked and Sorted on Catawiki](#)

¹¹For sold items, products have on average a final bidden price 45% and 57% lower than, respectively,

value-signalling by the platform may be an attempt to amplify the willingness to pay.

Among those objects that received an expert’s estimate and for which sellers were allowed to set a reserve price, 77% chose to do so. Despite Catawiki strongly incentivizing sellers not to set a reserve price when they are allowed to,¹² we see that the vast majority choose to do so anyway. 43% of objects ended up being sold.¹³ The number of bids and the number of bidders are more evenly distributed than final prices and estimates. While some objects perform extremely well, the median and the mean remain relatively close. As expected, we see that only a minor proportion of our listings were promoted in the cover images of their auction as there are only a few slots available¹⁴

2.3 Reserve Price

We know that receiving an estimation is a prerequisite for sellers to be able to set a reserve price. Considering only objects that were estimated by the experts, it can be interesting to compare those whose sellers ultimately chose to set a reserve price and those for which it was not the case. Table 2 provides a comparison in means for different variables.

As expected, those listings with a reserve price have larger estimates on average, suggesting that sellers might want to enjoy the insurance from the reserve price more when they are selling a more valuable object. Consistently, the value of the final bid is also slightly larger for those objects. However, the popularity is significantly more important for the “no reserve price” listings, which is consistent with Catawiki’s claims. Also and maybe more interestingly, we see that the platform obtains lower revenue per object on average in the group with a reserve price, despite these objects being more valuable.

From a preliminary review of our data, it becomes apparent why Catawiki encourages sellers to forgo setting a reserve price: it often results in objects not being sold, thereby yielding no profit for the platform. However, sellers do not decide on a reserve price arbitrarily; they do so because they have outside options. Consequently, a sale that does not occur due to a bid falling below the reserve price is not necessarily detrimental to the seller, although it is for Catawiki. This situation reveals a clear misalignment between the interests of the platform and those of the sellers. Catawiki’s recommendation to avoid setting a reserve price should not be accepted uncritically by sellers. Additionally, these

the minimum and maximum expert estimates. For sold items with a reserve price, products have on average a final bidden price 26% and 41% lower than, respectively, the minimum and maximum expert estimates.

¹²For example, see this webpage of Catawiki providing reasons for sellers not to set a reserve price : <https://archive.is/wip/wH1PA>. They argue that selling without a reserve price can lead to a guaranteed sale and often attracts more bidders, potentially resulting in higher final prices. Additionally, not setting a reserve price can create a more engaging bidding experience.

¹³On our full sample of estimated and non estimated objects, we find a similar proportion of sold objects to that announced by Catawiki on its website, with 69% of objects sold in our sample compared to 2/3 in general according to the platform, see: <https://archive.is/4utbB>. For a comparison of estimated and non estimated items, see Table 9 in Appendix 7.2.3.

¹⁴Four slots available at the time of data collection.

has Reserve Price	No	Yes
Number of Observations	13,417	43,784
Mean		
Final Bidden Price (€)	434.8	637.0
Platform Revenue (€)	96.5	28.4
Min. Estimate (€)	1,330	1,726
Max. Estimate (€)	1,585	2,003
Max./Min. Estimate Ratio	1.29	1.23
# of Bids	22.55	7.83
# of Bidders	8.50	3.98
Proportion		
is Sold	1.00	0.25

Note: The platform revenue is computed using the fees disclosed by Catawiki. For object i , it is equal to:

$$\mathbb{1}(\text{sold}_i = 1) \times ((0.125 + 0.09) \cdot p_i + 3)$$

Table 2: Mean Comparisons objects with or without Reserve Price

observations raise the possibility that Catawiki might strategically choose not to provide estimates for objects, thereby preventing sellers from setting reserve prices.

Despite the interesting nature of these aspects of experts' decisions, they are not the primary focus of this paper. Instead, we investigate whether buyers are influenced by expert estimates. Furthermore, we explore the potential gains the platform might derive from distorting these estimates. In this respect, sellers' and the platform's incentives are likely aligned.

3 Empirical Strategy

3.1 Descriptive Evidence

Our interest lies in understanding whether the experts' estimates provided by the platform can affect the behavior of buyers and sellers. This is not a trivial question because, on the one hand, users may be unsophisticated and eager to know more about the products they are considering to bid on. Sellers might refrain from setting a reserve price if the platform anticipates a sufficiently high demand for their good. On the other hand, the platform has an incentive to sell goods even if it does not make financial sense for the seller. This allows the platform to collect their commission. To do so, the platform's experts may want to steer buyers into bidding by raising its estimates. Yet, these short-term profit incentives for the platform must be weighed against the long-term interest in preserving the platform's reputation.

To conduct our analysis, we now introduce notations which we use repeatedly in our analyses. Consider an object listing i . We will focus on evaluating the impact of the expert estimates on its final bidden price is p_i . We will use two variables to summarize the experts' estimates:

- **Minimum estimate:** we will always use its natural logarithm and denote it by $\ln(e_i^{min})$. As shown below, we take this as a proxy variable for the value of a good.
- **Ratio of maximum to minimum estimates:** this is our main variable of interest. It is the ratio of the maximum expert estimate e_i^{max} to its minimum e_i^{min} , denoted as e_i^{max}/e_i^{min} . It represents the degree to which the average estimate is pushed up relative to its fundamentals.

We take the minimum estimate as a proxy for the value of a good on the basis that it is close to the final price of a good. To see this, Figure 3 plots a histogram of the final price over the two different types of estimates. The blue histogram has more mass close to one; the theoretical case where the final price is equal to the estimate. In contrast, the maximum estimate has an excess mass around 0.25 indicating that the maximum estimate largely over-estimates the final price. Given that the minimum estimate is already inflated compared to the final bidden price, the maximum estimate will be even more biased since it is further away. Therefore, if buyers should trust any information provided by the expert and use it as a proxy for the object's value, it should be the minimum estimation.

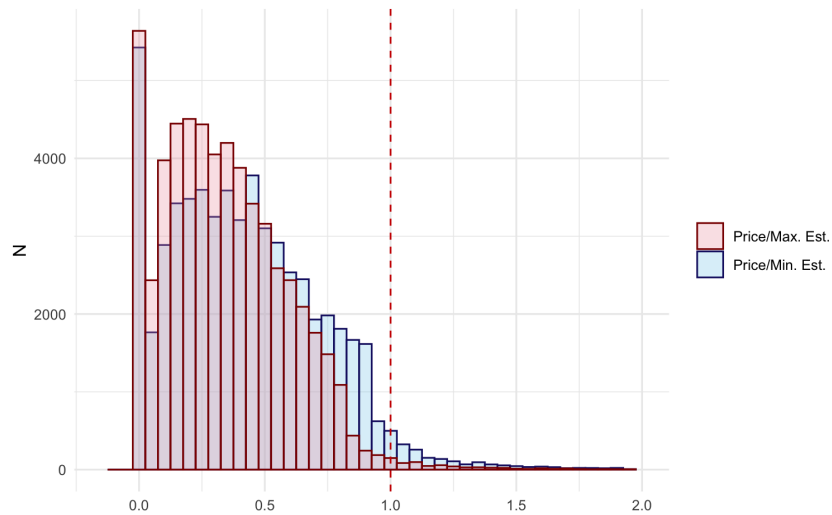


Figure 3: Distribution Comparison $\frac{\text{Price}}{\text{Max. Estimate}}$ vs. $\frac{\text{Price}}{\text{Min. Estimate}}$

As shown in Figure 4(a), the minimum estimate is highly correlated with the final price, suggesting it fulfils its role as a (biased) proxy variable for the good's final bid. This image shows a binned scatter-plot between the log minimum estimate and the log final bidden price. The 45 degree line is plotted in red. This line is nearly collinear to the line

summarizing the relationship between $\ln(p_i)$ and $\ln(e^{min})$. This indicates that the log minimum estimation evolves linearly with the log final price but is inflated by a constant factor as our observed prices are shifted down. This confirms that the estimate could be a good proxy for an object's value.

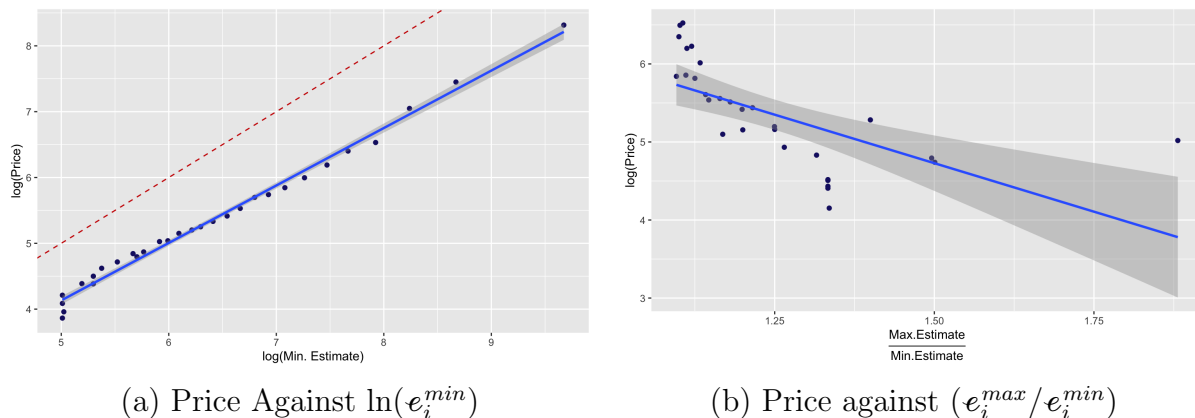


Figure 4: Estimates and Price

In contrast, Figure 4(b) suggests that the ratio of maximum to minimum expert estimates is negatively correlated with the final price. This comes from the fact that the ratio tends to decrease with the value of the minimum estimate, as shown in Figure 5(a). As such, to separate the effect of the ratio from the minimum estimate (and the value of the good), we need to account for it. A descriptive way to do so is to consider how $\ln(p_i/e_i^{min})$ behaves against the ratio of estimates e_i^{max}/e_i^{min} as it is akin to controlling for the linear effect of the minimum value. We display this relationship in Figure 5(b). There now appears to be a slight inverted-U shape pattern, as anticipated initially. As such, an increase in the ratio of maximum to minimum expert estimates appears to increase the final bidden price.

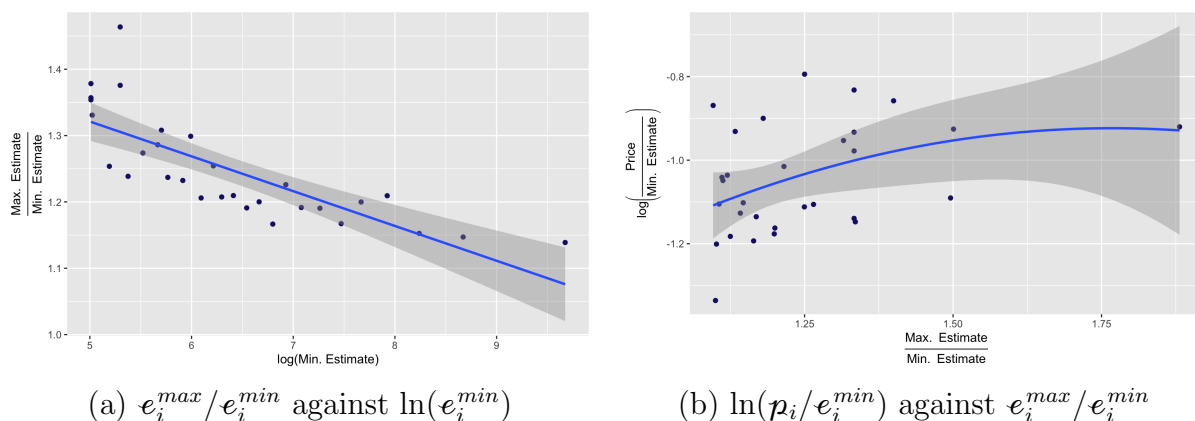


Figure 5: Comparison of Relations between Estimates

This descriptive analysis has some limitations. For one, the division of final bidden price to minimum estimate might be too constrictive to fully account for the good's

fundamental value. Second, these figures exploit purely cross-sectional variation and ignore potential confounders which stem from the nature of the auction or the identity of sellers or experts. Third, the inverted-U relationship may be non-significant from an economic or statistical point of view. To account for these possibilities, Section 3.2 below develops an econometric evaluation framework to relax these assumptions and which will allow us to test for the statistical significance of our findings as well as measure their magnitudes.

3.2 Evaluation Framework

We now formalize the insights from the previous sub-section in a regression framework. This will allow us to account for observable confounders as well as generalize the analysis to other dependent variables. To this end, let $i = 1, \dots, N$ denote our observational unit at the level of the listing for a unique object. Our main regression models is

$$y_i = \ln(e_i^{min}) \beta_1 + \ln(e_i^{min})^2 \beta_2 + (e_i^{max}/e_i^{min}) \tau_1 + (e_i^{max}/e_i^{min})^2 \tau_2 + \mathbf{x}_i' \boldsymbol{\theta} + \varepsilon_i \quad (3.1)$$

In this equation, y_i denotes our outcome variable. It is equal to (i) an indicator of the product attracting at least one bidder, $\mathcal{I}_i = \mathbb{1}(\# \text{ of Bidders}_i \geq 1)$, and (ii) the log of the final bidden price, $\ln(p_i)$. The latter is only defined when there is at least one bid so we estimate the model with the latter dependent variable by conditioning on the product having received at least one bid. e_i^{min} and e_i^{max} measure, respectively, the minimum and maximum price estimate made by the expert. As there are likely upper limits to the effects of increasing the expert estimates, we allow for non-linearity by including squared values. We control for the log of the minimum estimate as a proxy for the intrinsic characteristics of the good and do not treat the associated parameters as causal. As such, our main parameters of interest concern those related to the ratio of estimates which measure how, conditional on the lower estimate, the platform can affect behavior by raising expectations regarding the upper value of the good. As such, our main vector of parameters of interest is (τ_1, τ_2) . We denote observable control variables by \mathbf{x}_i . This vector is associated with the parameters $\boldsymbol{\theta}$. We provide specifications with seller fixed effects, auction (i.e, a lot of similar products sold at the same time) fixed effects and expert fixed effects. This allows us to further account for confounders. Finally, ε_i is the error term centered at zero. We cluster our standard errors by auction to account for heteroskedasticity and correlation of the error term within auctions.

3.3 Identification Strategy

Conditional Exogeneity. We first provide estimates under the assumption of conditional independence of the error term ε_i of Equation 3.1. This assumption is credible

to the extent that controlling for the lower expert estimate $\ln(e_i^{min})$ accounts for all unobservables which might be correlated with our main independent variable of interest, the ratio of estimates (e_i^{max}/e_i^{min}) . Relying on the unique setting provided by Catawiki, this lower estimate is credible to the extent that the lower estimate is proxy for the good’s value. Given that the final bidden price follows this value closely (Figure 4(a)), this assumption appears plausible. Estimates based on the conditional independence assumption are denoted by “Ordinary Least Squares Estimates” in the remainder of the text.

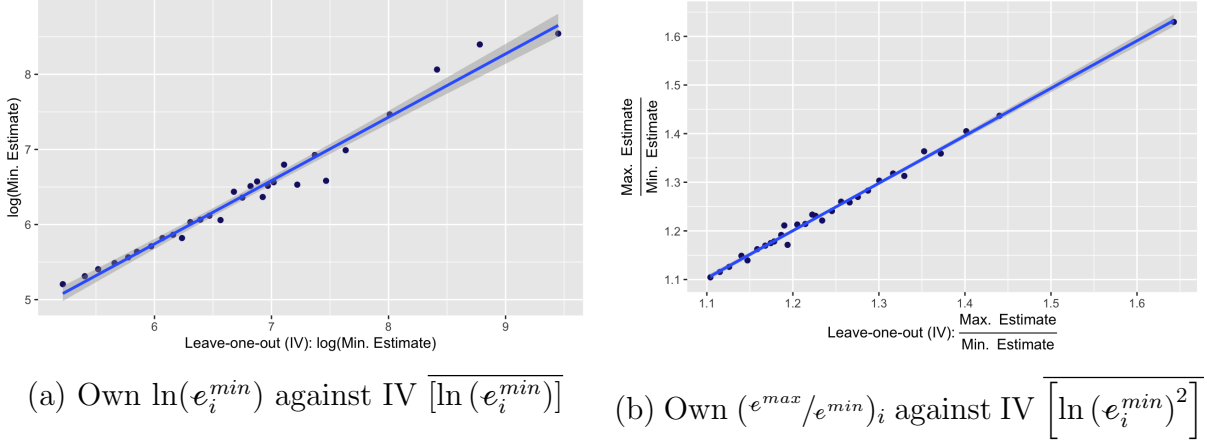


Figure 6: Expert-Day Leave One Out Instruments

Instrumental Variables. Second, we provide estimates relying on instrumental variables for identification. As we have seen in Figure 4(b), the ratio of estimates is correlated with the lower estimate. If there are product attributes unobserved to the econometrician and which are not correctly priced into the expert’s lower estimates (i.e, the lower estimate is an imperfect proxy variable), the ratio of estimates is potentially endogenous and ordinary least squares will result in an omitted variable bias.

To deal with this potential endogeneity, we construct instruments by exploiting the unique features of Catawiki. In particular, we leverage random variation arising in the day-to-day estimates made by experts in the form of an expert leave one out instrument. To do so, we identify the set of other products estimated on day t by i ’s expert $\mathcal{E}(i)$ denoted by $\mathcal{P}_{\mathcal{E}(i)}$ of cardinality $|\mathcal{P}_{\mathcal{E}(i)}|$. We then calculate multiple instruments in the form of distributional statistics to capture variation in the expert’s assessments across days. This is particularly useful to identify the curvature of the endogenous variables.

$$\begin{aligned}
 \overline{[\ln(e_i^{min})]} &:= (1/|\mathcal{P}_{\mathcal{E}(i)}|) \sum_{j \in \mathcal{P}_{\mathcal{E}(i)}} \ln(e_j^{min}) & \overline{[(e_i^{max}/e_i^{min})]} &:= (1/|\mathcal{P}_{\mathcal{E}(i)}|) \sum_{j \in \mathcal{P}_{\mathcal{E}(i)}} (e_j^{max}/e_j^{min}) \\
 \overline{[\ln(e_i^{min})^2]} &:= (1/|\mathcal{P}_{\mathcal{E}(i)}|) \sum_{j \in \mathcal{P}_{\mathcal{E}(i)}} \ln(e_j^{min})^2 & \overline{[(e_i^{max}/e_i^{min})^2]} &:= (1/|\mathcal{P}_{\mathcal{E}(i)}|) \sum_{j \in \mathcal{P}_{\mathcal{E}(i)}} (e_j^{max}/e_j^{min})^2
 \end{aligned} \tag{3.2}$$

The validity of these instruments rely on the experts having idiosyncratic variations in their day to day assessment of products (e.g, on a random good day, the expert over-values the low and high estimates) in a way which affects the final price only through the good’s expert estimates. Controlling by auction fixed effect, we take this variation to be quasi-random.¹⁵ The relevance of our instruments is illustrated by the binscatters of Figure 6 which shows a close linear relationship between the instruments and the endogenous variables. This suggests that when the expert provided a higher minimum estimate during a given day, one can expect other goods evaluated by this expert to also be more highly estimated.

We then estimate the following first-stage regressions for a two-stage least square procedure. For each of our four endogenous variables, which we denote using the representation $q_i \in \{\ln(e_i^{min}), \ln(e_i^{min})^2, (e_i^{max}/e_i^{min}), (e_i^{max}/e_i^{min})^2\}$, we run the following linear regression with our instruments,

$$q_i = \overline{[\ln(e_i^{min})]} \times \kappa_1 + \overline{[\ln(e_i^{min})^2]} \times \kappa_2 + \overline{[(e_i^{max}/e_i^{min})]} \times \kappa_3 + \overline{[(e_i^{max}/e_i^{min})^2]} \times \kappa_4 + \mathbf{x}_i\boldsymbol{\varphi} + \eta_i \quad (3.3)$$

The estimates are provided in Appendix 7.3.2.¹⁶ Table 11 reports the first-stage estimates for the sub-sample of products having received at least one bid. Each of our endogenous variables are statistically related to at least one unique instrument in the sense that they have coefficients which are statistically significant. Different instruments are statistically significant for different endogenous variables, suggesting that they capture different aspects of the randomness affecting expert analysis. These observations hold while controlling for auction, seller, and expert fixed effects. One can note that the F-stat is always above 10, indicating that the instruments are relevant (Angrist and Pischke, 2009). Having established our instruments as relevant, we now turn towards our main results.

4 Main Results

Based on the empirical strategy presented in Section 3, we now provide an econometric assessment of the effect of increasing the ratio of high to low estimate on (i) the probability to have at least one bidder ($\mathfrak{b}_i = \mathbb{1}(\# \text{ of Bidders}_i \geq 1)$) and, conditional on having at least one bidder (ii) the log final bidden price $\ln(\mathfrak{p}_i)$. Subsection 4.1 presents the estimates based on Equation 3.1 assuming conditional exogeneity. Subsequently, subsection 4.2 reports the estimates when the low estimate and the ratio are instrumented by expert-day leave one out instruments.

¹⁵This approach differs from the “judge leniency instrument variables” approach which rely on random assignment of the judge (Kling, 2006). In our case, we condition on the expert (with expert fixed effects) but look an inter-day variation in estimations.

¹⁶For the full sample, sub-section 7.3.2 reports Table 10

4.1 Ordinary Least Square Estimates

This section discusses the effect of an expert increasing the ratio of high to low estimates under the assumption of conditional exogeneity. The estimates of Equation 3.1 under ordinary least squares (OLS) are provided in Table 3 below. Focusing first on the effect of expert estimates on the probability that the good attracts at least one bidder, we observe across specifications (1) to (3) an absence of an effect related to the minimum expert estimate. In contrast, the linear term for the ratio of maximum to minimum expert estimates is associated with a positive and statistically significant coefficient estimate. The quadratic term is not statistically significant despite being of a negative sign, indicative of a U-shape pattern. The estimates are stable across specifications despite a loss of statistical significance perhaps attributable to the increase in the number of fixed-effects. These estimates suggest that for a product with a ratio of one (i.e, the same max and min estimate) which goes to two (i.e, the maximum estimate is now double the minimum estimate), the probability of attracting at least one bidder would increase by 3 probability points. Despite this effect being statistically significant, it is not economically significant, leading us to conclude that raising expectations about the value of a good does not increase the chances of attracting at least one bidder.

In contrast, there is a much more sizeable effect of raising expectations about the value of a good on the final bidden price, conditional on at least one bid having been submitted. This can be seen by assessing columns (4) to (6) in Table 3. Here, the ratio of estimates and its square are always statistically significant at 0.1% level of significance. The magnitudes do not qualitatively change across specifications. There is a clear inverted U-shape identified by the coefficient estimates. This indicates that raising the ratio of high to low estimates can increase the final bidden price up to an upper bar. In our preferred specification which has the most controls (column (6)), this upper bar is equal to $-0.305/(2 \times -0.022) \approx 7$. That is, the maximum log final price (conditional on having at least one bidder) is reached for a ratio of high to low estimate around 7. In practice, the average ratio of high to low estimates is around 1.25 (Table 1) suggesting that the platform is not setting expert estimates to the revenue maximizing level. To assess the magnitude of the estimated effects, we consider a good with an initial ratio of one (i.e, the same max and min estimate). Suppose it doubles (i.e, the maximum estimate is now double the minimum estimate) then the final expected price approximately increases by 23.9% (i.e, 0.522 - 0.283). As such, the platform appears to be able to raise final prices in an economically sizeable way.

4.2 Instrumental Variable Estimates

We now discuss our main findings based on using instrumental variables to identify the effect of increasing the ratio of maximum to minimum expert estimates. The parameter

	1(# of Bidders \geq 1)			log(Price)		
	(1)	(2)	(3)	(4)	(5)	(6)
log(Min. Estimate)	0.008 (0.011)	0.006 (0.011)	0.005 (0.013)	1.15*** (0.048)	1.16*** (0.047)	1.12*** (0.053)
log(Min. Estimate) square	-0.001 (0.0008)	-0.001 (0.0008)	-0.001 (0.0009)	-0.013*** (0.003)	-0.014*** (0.003)	-0.013*** (0.004)
Max./Min. Estimate	0.028* (0.013)	0.028* (0.014)	0.029* (0.015)	0.299*** (0.051)	0.333*** (0.051)	0.305*** (0.051)
Max./Min. Estimate square	-0.001 (0.001)	-0.001 (0.002)	-0.001 (0.002)	-0.021*** (0.004)	-0.024*** (0.004)	-0.022*** (0.004)
Observations	57,201	57,201	57,201	52,765	52,765	52,765
R ²	0.442	0.447	0.478	0.771	0.777	0.791
Within R ²	0.0009	0.001	0.001	0.469	0.441	0.364
Seller FE	✓	✓	✓	✓	✓	✓
Expert FE		✓	✓		✓	✓
Auction FE			✓			✓

Standard Errors in parentheses.

+: $p < 0.1$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Note: This table presents the regression output from a linear regression using the dummy variable equal to one if an object attracted at least one bidder as a dependent variable in columns (1) to (3) and using log(Price) as a dependent variable in columns (4) to (6). Each observation is an object listing. When log(Price) is the dependent variable, we restrict our dataset to objects that attracted at least one bidder. Standard Errors are clustered at the auction level. The log-linear specification lends itself to the following interpretation of the main coefficient of interest in column (6), our preferred specification: *ceteris paribus*, an increase from an initial ratio of estimates of 1 to a ratio of 2 increases the final expected price by $(0.522 - 0.283) \times 100 = 23.9\%$.

Table 3: The effect of experts' estimates on bidding and final price (OLS)

estimates obtained using two-stage least squares (2SLS) to estimate Equation 3.2, with the first stage derived from Equation 3.3, are provided in Table 4 below. Focusing first on the effect on the probability to have at least one bidder (columns (1) to (3)), we report that no coefficient is statistically or economically significant. This is in line with the findings made using ordinary least squares (Table 3). As such, we conclude that there is no effect of the ratio of expert estimates on the probability to attract at least one bidder.

We now turn our attention on the effect of the ratio of expert estimates on the final bidden price, conditional on having received at least one bid. As displayed in columns (4) to (6), there is again a clear inverted U-shape once auction fixed effects are accounted for. In our preferred specification with the most controls, the coefficient estimates of interest are statistically significant at the 0.1% level of significance and are almost equal to those obtained using ordinary least squares (Table 3).¹⁷ As such, they lead to the same interpretation: 7 is the upper bar to the ratio of estimates before which we can expect the

¹⁷In Appendix 7.3.1, Figure 7 displays the correlation matrix between the endogenous variables and instruments. There is no perfect correlation between these variables which would mechanically lead to the OLS and 2SLS estimates to be close.

	$\mathbb{1}(\# \text{ of Bidders} \geq 1)$			log(Price)		
	(1)	(2)	(3)	(4)	(5)	(6)
log(Min. Estimate)	0.062*	0.065	-0.005	1.29***	1.56***	1.10***
	(0.028)	(0.047)	(0.019)	(0.141)	(0.272)	(0.063)
log(Min. Estimate) square	-0.004 ⁺	-0.004	-0.0002	-0.016 ⁺	-0.029 ⁺	-0.011**
	(0.002)	(0.003)	(0.001)	(0.009)	(0.017)	(0.004)
Max./Min. Estimate	-0.002	0.168	-0.008	-0.105	1.02	0.308***
	(0.060)	(0.155)	(0.017)	(0.324)	(1.03)	(0.078)
Max./Min. Estimate square	0.013	-0.0006	0.002	0.011	-0.105	-0.022***
	(0.015)	(0.015)	(0.002)	(0.050)	(0.085)	(0.006)
Observations	57,201	57,201	57,201	52,765	52,765	52,765
R ²	0.434	0.439	0.478	0.768	0.770	0.791
Within R ²	-0.013	-0.013	0.0008	0.462	0.423	0.364
Seller FE	✓	✓	✓	✓	✓	✓
Expert FE		✓	✓		✓	✓
Auction FE			✓			✓

Standard Errors in parentheses.

+ : $p < 0.1$, * : $p < 0.05$, ** : $p < 0.01$, *** : $p < 0.001$.

Note: This table presents the regression output from an instrumental variable regression using the dummy variable equal to one if an object attracted at least one bidder as a dependent variable in columns (1) to (3) and using log(Price) as a dependent variable in columns (4) to (6). Each observation is an object listing. When log(Price) is the dependent variable, we restrict our dataset to objects that attracted at least one bidder. Standard Errors are clustered at the auction level. The log-linear specification lends itself to the following interpretation of the main coefficient of interest in column (6), our preferred specification: *ceteris paribus*, an increase from an initial ratio of estimates of 1 to a ratio of 2 increases the final expected price by $(0.528 - 0.286) \times 100 = 24.2\%$.

Table 4: The effect of experts' estimates on bidding and final price (2SLS)

final bidden price to fall. As before, if one considers a good with an initial ratio of one (i.e, the same max and min estimate) and suppose it doubles (i.e, the maximum estimate is now double the minimum estimate), then the final expected price approximately increases by 24.2% (i.e, 0.528 - 0.286). The similar findings from OLS and 2SLS lead us to conclude that the platform has access to tools, in the form of the maximum and minimum estimates, which can affect the final bidden price.

4.3 Robustness Checks.

Before looking into the economic mechanisms which could help explain our main findings, we briefly discuss some alternative specifications and robustness checks used to assess our empirical strategy and relegate the associated regression tables to Appendix 7.4.

4.3.1 Endogeneity

“Gallery” and “Retail” Estimates. A potential threat to identification lies in minimum expert estimate to be an unreliable proxy for the fundamental value of a product. We consider a subset of our observations where the estimate is based on “gallery” or “retail” prices. These estimates are only provided for visual artworks and jewellery (or precious estimates) but can be considered as the most objective form of estimate possible.¹⁸ We estimate Equation 3.1 in OLS and 2SLS and display the regression output in Tables 12 and 13 of Appendix 7.4.1. The results are very similar to those of our main tables 3 and 4. That is, we find an inverted-U shape of the effect of the ratio of maximum to minimum estimates on final bidden prices. Despite a sample which is six times smaller than for the main analysis, the 2SLS estimates are statistically significant at the 0.1% level of significance.

Placebo tests. To assess the validity of the empirical design, we estimate our main equation of interest (Equation 3.1) on outcomes on which we expect that the ratio of maximum to minimum expert estimates have no effect. To this end, we calculate the “Title Length” and the “Description Length” (in terms of the number of characters) for each product. We also identify the country of origin of each of the expert and create a dummy equal to one if the seller and expert share the same country, under the assumption that buyers should not care if both share this link. These variables are then used as dependent variables. The pertinence of these variables rests on them having a “reverse” effect on estimates : a more detailed and rich title/description are likely to increase the estimates. They may be a tendency of experts to give greater estimates to sellers from their own country. As such, the placebo tests will not trivially be passed. The estimates are provided in OLS and 2SLS in Appendix 7.4.2 in, respectively, Tables 14 and 15. In all three cases, there is an absence of a systematic and statistically significant effect for the ratio of maximum to minimum estimates on these placebo outcomes, corroborating the validity of the empirical design.

Fixed Product Characteristics. As a means to address unobserved heterogeneity in the characteristics of products, we would like to add to our main specification product fixed effects. For most products, this is unachievable. However, a subset of products share the exact same three images displayed in the same order on the product page. Identified by the shared url for these images, we can specify a model where we include fixed effects specific to each unique combination of the three same images in the exact same order. We take this specification as a good indication that the listings are selling the exact same product. We do so using the full sample of estimated listings in Table

¹⁸More information concerning these estimates are available in Appendix 7.1 which reproduces the description concerning the nature of expert estimates available on Catawiki.

16 in Appendix 7.4.3 using Pseudo-Poisson Maximum Likelihood (PPML) in order to specify a single model, which can be interpreted as the log-linear model, which preserves statistical power. Qualitatively speaking, we find the same patterns as before : the effect of the ratio of high to low estimates follows an inverted-U shape (column (1)). The coefficients are statistically significant at the 0.1% level. However, quantitatively speaking, the magnitudes are different : the ratio which maximises the revenue of the seller (and of the platform) is nearly 30% which is similar to the average ratio observed in the overall sample.

4.3.2 Statistical Power

Linear Specifications. The estimates based on Equation 3.1 are potentially under-powered. They require one to find four instruments for four endogenous variables. In Appendix 7.4.4, we provide estimates removing the quadratic terms as well as the instruments $\overline{[\ln(e_i^{min})^2]}$ and $\overline{[(e_i^{max}/e_i^{min})^2]}$. Tables 17 and 19 provide, respectively, the OLS and 2SLS estimates. As in the main tables 3 and 4, the 2SLS results report a ratio of maximum to minimum expert estimates coefficient which is positive and statistically significant (at the 5% level) for the final bidden price. For a product with at least one bid, doubling the ratio from one to two raises the expected final bidden price by approximately 10%.

Instrumenting only the ratio of estimates. As an alternative exercise, we consider a specification where we do not treat the log minimum expert estimate to be endogenous. We repeat our main analysis but do not instrument this term or its square, and remove as instruments $\overline{[\ln(e_i^{min})]}$ and $\overline{[\ln(e_i^{min})^2]}$. The 2SLS results are provided in Appendix 7.4.5 in Table 20. The results are virtually unchanged compared to those in our main analysis (Tables 3 and 4).

Specifications with zero sales. In order to increase statistical power, we considered specifications which allowed us to include zeros in the dependent variable. In doing so, we no longer condition on having at least one bidder as in Table 3. Given that the log of zero is not defined, we rely on Poisson-Pseudo Maximum Likelihood (PPML) which is an exponential conditional mean model which also allows for zeros in the dependent variable. Estimates are provided in Table 21 in Appendix 7.4.6. Qualitatively speaking, the results are unchanged. We find an inverted-U shaped effect of the ratio of high to low estimates on both the final price and the number of bidders. For the former dependent variable, this indicates that the expected revenue of the seller increases up to an upper limit in terms of the ratio of high to low estimates.

5 Economic Mechanisms

Section 4 provided evidence that raising the ratio of high to low estimates made by the expert can affect the final bidden price. We now explore the mechanisms which could explain this result. In sub-section 5.1, we show that a higher ratio of maximum to minimum expert estimates impacts supply through seller behavior. We see that it lowers the probability of setting a reserve price and increases the prominence of the product on the platform. In turn, the number of bids and bidders increases. Then, in sub-section 5.2, we show that keeping the presence of a reserve price, number of bids, and number of bidders fixed, we still find that final bidden price increases, suggesting also an effect on product demand. As such, the ratio of high to low expert estimates appears to affect equilibrium prices through both product supply and demand.

5.1 Impact through Supply Decisions

We now consider how the ratio of maximum to minimum expert estimates affects suppliers. The most important decision that can take the supplier is to set a reserve price or not, as a higher reserve price can lower the probability of selling a good, but can save the seller from making a transaction below her reservation value. To assess the impact of the ratio on the probability of setting a reserve price, we estimate Equation 3.1 using OLS and 2SLS but using the presence of a reserve price as the dependent variable.

	has Reserve Price (1)	is Sold (2)	log(Rank) (3)	is Promoted (4)	# of Bids (5)
log(Min. Estimate)	0.200*** (0.037)	-0.215*** (0.044)	0.040 (0.122)	0.044 (0.042)	0.813 (0.835)
log(Min. Estimate) square	-0.009*** (0.003)	0.008* (0.003)	-0.018* (0.009)	0.006+ (0.003)	-0.0002 (0.060)
Max./Min. Estimate	-0.122*** (0.029)	0.242*** (0.044)	-0.171 (0.106)	0.065+ (0.038)	1.62* (0.731)
Max./Min. Estimate square	0.009*** (0.002)	-0.016*** (0.003)	0.014 (0.009)	-0.005+ (0.003)	-0.091 (0.057)
Observations	57,201	57,201	57,201	57,201	57,201
R ²	0.755	0.523	0.412	0.225	0.561
Within R ²	0.047	0.031	0.020	0.041	0.004
Seller FE	✓	✓	✓	✓	✓
Expert FE	✓	✓	✓	✓	✓
Auction FE	✓	✓	✓	✓	✓

Standard Errors in parentheses.

+: $p < 0.1$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Note: This table presents the regression output from an instrumental variable regression using in (1) a dummy equal to one if the object has a reserve price, in (2) a dummy equal to one if the object was ultimately sold, in (3) the log(Rank), in (4) a dummy equal to one if the object was promoted and in (5) the number of bids the object received as a dependent variable. Each observation is an object listing. Standard Errors are clustered at the auction level. The interpretation of the main coefficients of interest in column (1) is, *ceteris paribus*, that an increase of the ratio of estimates from 1 to 2 decreases the probability of the seller setting a reserve price by approximately 17.6 probability points. In column (2), the interpretation of the main coefficients of interest is that an increase of the ratio of estimates from 1 to 2 increases the probability to sell the object by approximately 19.4 probability points.

Table 5: The effects of experts' estimates on alternative outcomes (2SLS)

The results for the 2SLS estimates are provided in column (1) of Table 5. The OLS estimates are virtually the same (but with smaller standard errors) and are available in Table 22 of Appendix 7.5.1. We report a negative and statistically significant coefficient associated with the linear effect of the ratio of maximum to minimum expert estimates. This indicates that a ratio going from one to two would lower the probability of setting a reserve price by approximately 18 probability points. This sizeable economic effect indicates that suppliers are also affected by the experts' assessments. At the same time, column (3) shows that products with a higher ratio are more likely to be among the first products displayed (lower auction rank) and are more likely to be promoted in the auction cover images, as shown in column (4).¹⁹ As a consequence, we find that going from a ratio of one to two increases the expected number of bids by approximately 1.5 (column (5)). Naturally, column (2) indicates that increasing this ratio leads to an economically and statistically significant increase in the probability of selling a product. In particular, a product changing its ratio from one to two would increase the probability of sale by approximately 19 probability points. As such, we can explain part of our results based on the ratio of high to low estimates affecting supplier decisions to lower the probability

¹⁹Although the coefficient in columns (3) and (4) are non-statistically significant, the estimates based on OLS in Table 22 are virtually the same but statistically significant.

of a reserve price, which, in turn, lead to more entry, and therefore more sales.

5.2 Impact through Demand Shifting

Having considered the effect of expert estimates on supply decisions, we now assess if the ratio of maximum to minimum expert estimates shifts demand. That is, we study if the willingness to pay for the product rises, keeping supply factors fixed. To see this, we estimate Equation 3.1 using the logarithm of the final bidden price as a dependent variable, but control successively for the number of bidders, the number of bids, and the presence of a reserve price. In doing so, we aim to keep supply decisions and competition fixed. Table 6 displays the results for the 2SLS estimates for products having received at least one bid.

This table indicates that, even when one conditions on a fixed numbers of bids, bidders, and the presence of a reserve price, the ratio of maximum to minimum expert estimates still increases the final bidden price. Indeed, a product switching from a ratio of one to two, would see its bidden final price increase by approximately 24.5 %. We interpret this finding as evidence that the final bidden price also increases due to a higher willingness to pay from consumers. In turn, these consumers are more likely to enter the auction for a product (see column (5) of Table 5).

6 Conclusion

This article shows that expert estimates provided by a digital auction platform can impact behavior of buyers and sellers. In particular, increasing the expectation of the maximum value of a good can raise the final bidden price. We explain this finding based on both buyer and seller behavior. Sellers have a significantly lower probability to use a reserve price when the ratio of maximum to minimum estimates rise. In turn, the platform promotes these goods more which leads to more buyers entering the product auction. Buyers have a higher willingness to pay for goods with a higher expectation of value, leading them to enter more auctions and bid more. As such, despite potential conflicts of interest between platforms and users, we show that the former can affect the beliefs and behavior of the latter agents.

	log(Price)		
	(1)	(2)	(3)
log(Min. Estimate)	1.12*** (0.065)	1.06*** (0.064)	0.968*** (0.063)
log(Min. Estimate) square	-0.013** (0.004)	-0.009* (0.004)	-0.005 (0.004)
Max./Min. Estimate	0.301*** (0.078)	0.271*** (0.071)	0.314*** (0.071)
Max./Min. Estimate square	-0.021*** (0.006)	-0.020*** (0.005)	-0.023*** (0.005)
# of Bidders	0.024*** (0.002)	-0.029*** (0.002)	-0.025*** (0.002)
# of Bids		0.029*** (0.001)	0.033*** (0.001)
has Reserve Price			0.421*** (0.024)
Observations	52,765	52,765	52,765
R ²	0.793	0.804	0.808
Within R ²	0.371	0.404	0.416
Seller FE	✓	✓	✓
Expert FE	✓	✓	✓
Auction FE	✓	✓	✓

Standard Errors in parentheses.

+: $p < 0.1$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Note: This table presents the regression output from an instrumental variable regression using log(Price) as a dependent variable. Each observation is an object listing. We restrict our dataset to objects that attracted at least one bidder. Standard Errors are clustered at the auction level. There are 3 object level control variables: the number of bidder, the number of bids and a dummy variable equal to one if a reserve price was set. The log-linear specification lends itself to the following interpretation of the main coefficient of interest in column (3), our preferred specification: *ceteris paribus*, an increase from an initial ratio of estimates of 1 to a ratio of 2 increases the final expected price by $(0.534 - 0.29) \times 100 = 24.4\%$.

Table 6: The effect of experts' estimates on final price, controlling for competition (2SLS)

7 Appendices

7.1 Expert Estimates

In this section, we reproduce the description provided by Catawiki regarding how expert estimates are made. The original source can be found at <https://archive.is/iILbd>.

What is the 'Expert's estimate'?

Some special objects on our online marketplace come with an estimate, indicated by our experts. The estimated price range functions as a guide for prospective buyers to assist them with determining the appropriate amount to bid for an object.

How is the 'expert estimate' determined? Our experts aim to determine the potential final bid value of objects offered for sale on our online marketplace. The estimate is based on both publicly (for example other online platforms or pricing websites) and privately (for example, historical sales data) available information. To establish market demand, experts consider a variety of factors, including but not limited to the following:

- artist or maker
- country of origin
- period
- provenance
- materials
- dimensions
- rarity
- subject matter or type, and/or
- condition

It should be noted that our experts do not carry out any physical inspections of the objects sold on our online marketplace. This means that for some information, such as for example the condition of an object, we rely on the accuracy of the information provided to us by our sellers.

Read more about the role of our experts here.

Specific types of 'expert estimates' For certain objects, our experts use a specific estimation tailored to the specific properties of these types of objects. If such a specific estimation is provided, it is indicated on the object page.

‘Gallery estimates’:

Gallery estimates are displayed specifically for some but not all visual artworks sold on our online marketplace. Our experts provide price ranges displayed in both online and physical galleries for similar artworks by the relevant artist in question as a factor to determine an estimate.

To establish a gallery estimate, our experts consider the following factors:

- artist or maker
- country of origin
- provenance
- materials
- dimensions
- rarity, and/or
- quality

‘Retail estimates’:

Retail estimates are sometimes displayed for the (modern) jewellery and precious stone objects sold on our online marketplace. Retail estimates are determined using the recommended retail price ranges of comparable objects sold by both the online and physical retailers as a factor.

To establish a retail estimate, our experts consider the following factors:

- artist or maker
- country of origin
- provenance
- materials
- dimensions
- rarity
- subject matter or type
- condition, and/or
- quality

To establish a retail estimate for precious stones, our experts consider the following:

- country of origin

- provenance
- treatment
- dimensions
- rarity
- subject matter or type, and/or
- quality

In order to have a good overview of these characteristics, we rely on the grading details that can be found on the reports of the Gemmological Laboratories. These reports play an essential role in outlining important details about the nature of the precious stone and may therefore influence the estimation process. The Gemmological Laboratories are independent entities and therefore Catawiki does not guarantee and accepts no responsibility for the accuracy, terms or information contained in the laboratory reports.

Please note that if an object is not accompanied by a report from a Gemmological Laboratory that states that the precious stone is natural and untreated, we will assume that some form of treatment may have been used and that such treatment may not be permanent. Our estimates reflect this assumption.

The expert estimate is not a guarantee.

When placing a bid on an object, your intrinsic and personal value for such an object should be the leading consideration. If however the market value of an object is important to you, we advise you to consult your own appraiser for taxation. Please be aware that purchasing objects for investment purposes or speculative purposes poses risks.

An estimate by definition cannot be relied upon as indicating the (objective) value of an object. Due to the nature of (online) auctions, there may be significant differences between the estimate and the eventual purchase price. Therefore, our estimates cannot be interpreted as indicating or guaranteeing the value of an object. For example, a third party appraiser might indicate a different value than our estimate or, in case of a resale, you might not receive an amount corresponding to our estimated value.

Catawiki can never be held liable whatsoever in the event that objects are sold for more or less than the estimated amount.

7.2 Data and Sample Statistics

7.2.1 Objects dataset summary

Total Number	
Objects	57,201
Sellers	5,407
Auctions	1,681
Experts	233

Table 7: Summary of the objects dataset

7.2.2 Categories

Category	Number of Products	Number of Auctions
Jewellery & Precious Stones	11,126	253
Interiors & Decorations	11,030	338
Art	7,910	160
Fashion	5,581	88
Watches	5,225	167
Archaeology & Natural History	3,852	60
Coins & Stamps	3,627	112
Wine & Whisky	2,072	120
Books & Comics	1,720	83
Asian & Tribal Art	1,287	38
Music & Cameras	980	58
Entertainment, Cards & Games	900	64
Toys & Models	858	60
Classic Cars, Motorcycles & Automobilia	626	48
Sports	352	20

Table 8: List of Main Categories and characteristics

7.2.3 Not Estimated Objects vs. Estimated Objects

is Estimated	No	Yes
Number of Observations	53,498	62,814
Mean		
Final Bidden Price (€)	82	613
Platform Revenue (€)	21	46
Min. Estimate (€)	-	1,642
Max. Estimate (€)	-	1,916
Max./Min. Estimate Ratio	-	1.25
# of Bids	14.8	11.2
# of Bidders	6.1	5.0
Proportion		
is Sold	0.99	0.44
has Reserve Price	0	0.77

Table 9: Mean Comparisons between Estimated and non-Estimated objects

As expected, the objects that did not receive an estimation ended up being largely less valuable from the buyers' perspective, as they have lower final bids on average. It was to be expected as it is the spirit of this experts' estimates, that can never be given to objects which they value at less than €150. We can be reminded that sellers of estimated objects set a reserve price 77% of the time which had a significant impact on the proportion of sold items. Indeed, we can see that in the group of non-estimated objects, pretty much every single one of them was ultimately sold i.e. received a bid of at least €1. Conversely, the presence of a reserve price in more than 2/3 of the estimated listings led to a drop in the proportion of sold objects to 44%, as the final bid can have not met the reserve price set by the sellers. It also has a impact on the platform's average revenue per listing, as they are only twice as large in the estimated group despite those product being allegedly significantly more valuable. In terms of popularity however, listings in the two groups are rather similar.

7.3 Instrumental Variables Estimation

7.3.1 Correlation Matrix

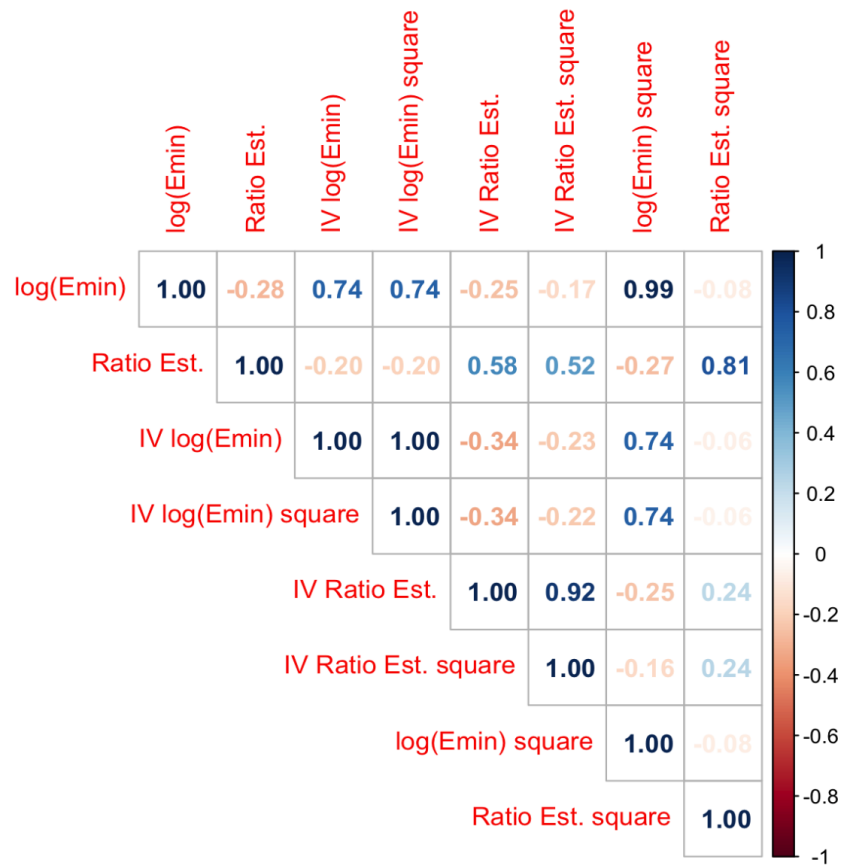


Figure 7: Correlation Matrix: Endogenous Variables and Instruments

7.3.2 First Stage Estimates

Full Sample

	log(Min. Estimate) (1)	log(Min. Estimate) square (2)	Max./Min. Estimate (3)	Max./Min. Estimate square (4)
$\overline{[\ln(e_i^{min})]}$	13.7 (12.8)	633.1** (203.9)	-1.19 (1.14)	4.42 (4.47)
$\overline{[\ln(e_i^{min})^2]}$	-3.68*** (0.953)	-84.4*** (15.7)	0.121+ (0.073)	-0.173 (0.275)
$\overline{[(e_i^{max}/e_i^{min})]}$	0.990 (4.83)	27.3 (63.9)	-6.94 (4.56)	254.7*** (34.9)
$\overline{[(e_i^{max}/e_i^{min})^2]}$	-0.192 (0.396)	-3.64 (5.26)	-6.24*** (1.06)	-112.9*** (12.0)
Observations	57,201	57,201	57,201	57,201
R ²	0.880	0.879	0.791	0.820
Within R ²	0.365	0.377	0.571	0.774
F (Kleibergen-Paap)	65.8	67.3	55.0	45.5
Seller FE	✓	✓	✓	✓
Expert FE	✓	✓	✓	✓
Auction FE	✓	✓	✓	✓

Standard Errors in parentheses.

+: $p < 0.1$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Note: This table presents the regression output from a linear regression using our exogenous variables as dependent variables: log(Min. Estimate) in column (1), the square of log(Min. Estimate) in column (2), the ratio of estimates in column (3) and the square of the ratio of estimates in column (4). Each observation is an object listing. Standard Errors are clustered at the auction level. We use our four leave one out instruments defined in Equation 3.2. Dependent variables are statistically related to at least one unique instrument in the sense that they have coefficients which are statistically significant. Different instruments are statistically significant for different endogenous variables. The F-statistics are above 10, indicating instrument relevance.

Table 10: First-Stage Estimates (Whole sample)

Sample with at least one bidder

	log(Min. Estimate) (1)	log(Min. Estimate) square (2)	Max./Min. Estimate (3)	Max./Min. Estimate square (4)
$\overline{[\ln(e_i^{min})]}$	8.14 (13.3)	558.5** (211.4)	-1.17 (1.21)	4.55 (4.77)
$\overline{[\ln(e_i^{min})^2]}$	-3.32*** (0.977)	-79.3*** (16.1)	0.120 (0.077)	-0.178 (0.292)
$\overline{[(e_i^{max}/e_i^{min})]}$	-0.612 (4.88)	8.53 (64.8)	-6.50 (4.76)	257.2*** (37.4)
$\overline{[(e_i^{max}/e_i^{min})^2]}$	-0.106 (0.401)	-2.67 (5.34)	-6.30*** (1.10)	-113.2*** (12.7)
Observations	52,765	52,765	52,765	52,765
R ²	0.883	0.882	0.794	0.821
Within R ²	0.372	0.383	0.573	0.768
F (Kleibergen-Paap)	58.0	59.2	50.1	39.0
Seller FE	✓	✓	✓	✓
Expert FE	✓	✓	✓	✓
Auction FE	✓	✓	✓	✓

Standard Errors in parentheses.

+: $p < 0.1$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Note: This table presents the regression output from a linear regression using our exogenous variables as dependent variables: log(Min. Estimate) in column (1), the square of log(Min. Estimate) in column (2), the ratio of estimates in column (3) and the square of the ratio of estimates in column (4). Each observation is an object listing. This table was generated on observations with at least one bidder. Standard Errors are clustered at the auction level. We use our four leave one out instruments defined in Equation 3.2. Dependent variables are statistically related to at least one unique instrument in the sense that they have coefficients which are statistically significant. Different instruments are statistically significant for different endogenous variables. The F-statistics are above 10, indicating instrument relevance.

Table 11: First-Stage Estimates (# of Bidders ≥ 1)

7.4 Robustness Checks

7.4.1 Gallery and Retail Estimates only

Ordinary Least Squares Estimates

	1(# of Bidders \geq 1)			log(Price)		
	(1)	(2)	(3)	(4)	(5)	(6)
log(Min. Estimate)	-0.008 (0.027)	8.78×10^{-5} (0.029)	-0.006 (0.028)	0.970*** (0.133)	1.00*** (0.136)	0.954*** (0.151)
log(Min. Estimate) square	-0.0010 (0.002)	-0.002 (0.002)	-0.001 (0.002)	-0.009 (0.008)	-0.011 (0.008)	-0.008 (0.009)
Max./Min. Estimate	0.012 (0.024)	0.020 (0.026)	0.029 (0.027)	0.439*** (0.119)	0.567*** (0.124)	0.514*** (0.121)
Max./Min. Estimate square	-0.001 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.038*** (0.010)	-0.047*** (0.010)	-0.044*** (0.010)
Observations	8,817	8,817	8,817	8,371	8,371	8,371
R ²	0.437	0.440	0.489	0.793	0.797	0.810
Within R ²	0.006	0.008	0.006	0.488	0.441	0.356
Seller FE	✓	✓	✓	✓	✓	✓
Expert FE		✓	✓		✓	✓
Auction FE			✓			✓

Standard Errors in parentheses.

+: $p < 0.1$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Note: This table presents the regression output from a linear regression using the dummy variable equal to one if an object attracted at least one bidder as a dependent variable in columns (1) to (3) and using log(Price) as a dependent variable in columns (4) to (6). Each observation is an object listing, that received either a “Gallery” or a “Retail” estimate, and not an “Expert” estimate. When log(Price) is the dependent variable, we restrict our dataset to objects that attracted at least one bidder. Standard Errors are clustered at the auction level. The log-linear specification lends itself to the following interpretation of the main coefficient of interest in column (6), our preferred specification: *ceteris paribus*, an increase from an initial ratio of estimates of 1 to a ratio of 2 increases the final expected price by $(0.852 - 0.47) \times 100 = 35.5\%$.

Table 12: Gallery and Retail Estimates only - Effect of Estimation (OLS)

Instrumental Variables Estimates

	$\mathbb{1}(\# \text{ of Bidders} \geq 1)$			log(Price)		
	(1)	(2)	(3)	(4)	(5)	(6)
log(Min. Estimate)	-0.230 (0.304)	0.135 (0.159)	0.023 (0.031)	-0.371 (1.67)	0.879 (1.22)	1.08*** (0.161)
log(Min. Estimate) square	0.014 (0.019)	-0.012 (0.011)	-0.002 (0.002)	0.077 (0.107)	0.008 (0.085)	-0.014 (0.010)
Max./Min. Estimate	0.586 (2.09)	-0.149 (0.103)	0.032 (0.028)	8.38 (14.6)	2.61 (1.92)	0.526*** (0.150)
Max./Min. Estimate square	-0.206 (0.653)	0.021 (0.022)	-0.003 (0.002)	-2.64 (4.50)	-0.519 (0.476)	-0.045*** (0.012)
Observations	8,817	8,817	8,817	8,371	8,371	8,371
R ²	-0.443	0.431	0.488	-5.14	0.647	0.809
Within R ²	-1.54	-0.008	0.005	-14.2	0.027	0.356
Seller FE	✓	✓	✓	✓	✓	✓
Expert FE		✓	✓		✓	✓
Auction FE			✓			✓

Standard Errors in parentheses.

+: $p < 0.1$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Note: This table presents the regression output from an instrumental variable regression using the dummy variable equal to one if an object attracted at least one bidder as a dependent variable in columns (1) to (3) and using log(Price) as a dependent variable in columns (4) to (6). Each observation is an object listing, that received either a “Gallery” or a “Retail” estimate, and not an “Expert” estimate. When log(Price) is the dependent variable, we restrict our dataset to objects that attracted at least one bidder. Standard Errors are clustered at the auction level. The log-linear specification lends itself to the following interpretation of the main coefficient of interest in column (6), our preferred specification: *ceteris paribus*, an increase from an initial ratio of estimates of 1 to a ratio of 2 increases the final expected price by $(0.0.872 - 0.481) \times 100 = 39.1\%$.

Table 13: Gallery and Retail Estimates only - Effect of Estimation (2SLS)

7.4.2 Placebo Test

Ordinary Least Squares Estimates

	Title Length (1)	Description Length (2)	Seller - Expert Country Dummy (3)
log(Min. Estimate)	6.07*** (1.70)	24.3 (24.0)	-0.011 (0.013)
log(Min. Estimate) square	-0.202+ (0.116)	0.639 (1.71)	0.0006 (0.0009)
Max./Min. Estimate	0.953 (1.94)	40.1 (27.3)	0.027 (0.017)
Max./Min. Estimate square	-0.090 (0.145)	-5.03* (2.52)	-0.003+ (0.001)
Observations	57,201	57,201	57,201
R ²	0.666	0.630	0.803
Within R ²	0.005	0.003	0.0003
Seller FE	✓	✓	✓
Expert FE	✓	✓	✓
Auction FE	✓	✓	✓

Standard Errors in parentheses.

+: $p < 0.1$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Note: This table presents the regression output from a linear regression using as a dependent variable: the number of character in the title and subtitle of a listing in (1), the number of character in the description of a listing in (2) and a dummy variable equal to one if the seller and the expert originate from the same country. Each observation is an object listing. Standard Errors are clustered at the auction level. Our coefficients of interests are never statistically at the 5% level in any of the three specifications.

Table 14: Placebo Test (OLS)

Instrumental Variables Second Stage Estimates

	Title Length (1)	Description Length (2)	Seller - Expert Country Dummy (3)
log(Min. Estimate)	8.84** (2.91)	-8.29 (41.3)	0.017 (0.022)
log(Min. Estimate) square	-0.386* (0.195)	3.13 (2.89)	-0.002 (0.002)
Max./Min. Estimate	-0.953 (3.95)	13.9 (48.1)	0.036 (0.024)
Max./Min. Estimate square	-0.017 (0.279)	-3.80 (3.92)	-0.003 (0.002)
Observations	57,201	57,201	57,201
R ²	0.666	0.630	0.803
Within R ²	0.005	0.003	3.55×10^{-5}
Seller FE	✓	✓	✓
Expert FE	✓	✓	✓
Auction FE	✓	✓	✓

Standard Errors in parentheses.

+: $p < 0.1$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Note: This table presents the regression output from an instrumental variable regression using as a dependent variable: the number of character in the title and subtitle of a listing in (1), the number of character in the description of a listing in (2) and a dummy variable equal to one if the seller and the expert originate from the same country. Each observation is an object listing. Standard Errors are clustered at the auction level. Our coefficients of interests are never statistically at the 5% level in any of the three specifications.

Table 15: Placebo Test (2SLS)

7.4.3 Product Fixed Effects

	Price (1)	has Reserve Price (2)	# of Bidders (3)
log(Min. Estimate)	-3.04*** (1×10^{-5})	0.918*** (1×10^{-5})	-10.4*** (1×10^{-5})
log(Min. Estimate) square	0.189*** (1×10^{-5})	-0.060*** (1×10^{-5})	0.962*** (1×10^{-5})
Max./Min. Estimate	5.09*** (1×10^{-5})	0.343*** (1×10^{-5})	6.14*** (1×10^{-5})
Max./Min. Estimate square	-1.92*** (1×10^{-5})	-0.149*** (1×10^{-5})	-2.40*** (1×10^{-5})
Observations	52,854	43,818	52,854
Squared Correlation	1.00	0.521	0.995
Pseudo R ²	0.996	0.0003	0.429
Seller FE	✓	✓	✓
Expert FE	✓	✓	✓
Auction FE	✓	✓	✓
Product Images FE	✓	✓	✓

+: $p < 0.1$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$; *SE clustered by Auction*

Standard Errors in parentheses.

+: $p < 0.1$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Note: This table presents the regression output from a Poisson Pseudo Maximum Likelihood (PPML) regression using as dependent variable the final price, a dummy equal to one if the product has a reserve price, and the number of bidders. Each observation is an object listing. Each specification includes seller, expert, auction and product images fixed effects. The latter are common for products which have the same images displayed in the same order. Standard Errors are clustered at the auction level.

Table 16: PPML Estimates with Product Fixed Effects

7.4.4 Linear Specification

Ordinary Least Square Estimates

	$\mathbb{1}(\# \text{ of Bidders} \geq 1)$			$\log(\text{Price})$		
	(1)	(2)	(3)	(4)	(5)	(6)
log(Min. Estimate)	-0.008*** (0.002)	-0.010*** (0.002)	-0.011*** (0.002)	0.964*** (0.008)	0.957*** (0.008)	0.930*** (0.010)
Max./Min. Estimate	0.014* (0.006)	0.014* (0.006)	0.015* (0.007)	0.085** (0.029)	0.091** (0.030)	0.078** (0.030)
Observations	57,201	57,201	57,201	52,765	52,765	52,765
R ²	0.442	0.447	0.478	0.771	0.777	0.790
Within R ²	0.0009	0.001	0.001	0.468	0.440	0.364
Seller FE	✓	✓	✓	✓	✓	✓
Expert FE		✓	✓		✓	✓
Auction FE			✓			✓

Standard Errors in parentheses.

+: $p < 0.1$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Note: This table presents the regression output from a linear regression using the dummy variable equal to one if an object attracted at least one bidder as a dependent variable in columns (1) to (3) and using $\log(\text{Price})$ as a dependent variable in columns (4) to (6). Each observation is an object listing. When $\log(\text{Price})$ is the dependent variable, we restrict our dataset to objects that attracted at least one bidder. Standard Errors are clustered at the auction level. The log-linear specification lends itself to the following interpretation of the main coefficient of interest in column (6), our preferred specification: *ceteris paribus*, a unit increase in the ratio of estimates increases the final expected price by approximately 7.8%.

Table 17: Linear Specification (OLS)

Instrumental Variables Estimates

First Stage Estimates.

	<i>Whole Sample</i>		<i>At Least One Bidder</i>	
	log(Min. Estimate)	Max./Min. Estimate	log(Min. Estimate)	Max./Min. Estimate
	(1)	(2)	(3)	(4)
$\overline{[\ln(e_i^{min})]}$	-35.4*** (2.42)	-0.795+ (0.482)	-36.2*** (2.63)	-0.821+ (0.498)
$\overline{[(e_i^{max}/e_i^{min})]}$	-5.39 (3.29)	-41.3*** (6.76)	-6.07+ (3.30)	-41.5*** (6.85)
Observations	57,201	57,201	52,765	52,765
R ²	0.876	0.698	0.880	0.702
Within R ²	0.345	0.380	0.355	0.380
F (Kleibergen-Paap)	107.5	35.6	95.4	33.4
Seller FE	✓	✓	✓	✓
Expert FE	✓	✓	✓	✓
Auction FE	✓	✓	✓	✓

Standard Errors in parentheses.

+: $p < 0.1$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Note: This table presents the regression output from a linear regression using our exogenous variables as dependent variables: log(Min. Estimate) in column (1) and (2) and the ratio of estimates in column (3) and (4). Each observation is an object listing. Columns (1) and (2) were generated using the whole sample, and columns (3) and (4) were generated using listing that attracted at least one bidder. Standard Errors are clustered at the auction level. The F statistics are obtained with the Kleibergen-Paap Wald test. We use our two of our leave one out instruments defined in Equation 3.2. Dependent variables are statistically related to at least one unique instrument in the sense that they have coefficients which are statistically significant. Different instruments are statistically significant for different endogenous variables. The F-statistics are above 10, indicating instrument relevance.

Table 18: First Stage Estimates - Linear Specification (2SLS)

Second Stage Estimates.

	$\mathbb{1}(\# \text{ of Bidders} \geq 1)$			log(Price)		
	(1)	(2)	(3)	(4)	(5)	(6)
log(Min. Estimate)	0.010** (0.004)	0.012 (0.012)	-0.007* (0.003)	1.06*** (0.021)	1.17*** (0.076)	0.938*** (0.011)
Max./Min. Estimate	0.026 (0.035)	0.161 (0.221)	0.006 (0.008)	-0.089 (0.243)	1.32 (1.41)	0.102* (0.042)
Observations	57,201	57,201	57,201	52,765	52,765	52,765
R ²	0.440	0.439	0.478	0.768	0.753	0.790
Within R ²	-0.002	-0.013	0.0009	0.462	0.381	0.364
Seller FE	✓	✓	✓	✓	✓	✓
Expert FE		✓	✓		✓	✓
Auction FE			✓			✓

Standard Errors in parentheses.

+: $p < 0.1$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Note: This table presents the regression output from an instrumental variable regression using the dummy variable equal to one if an object attracted at least one bidder as a dependent variable in columns (1) to (3) and using log(Price) as a dependent variable in columns (4) to (6). Each observation is an object listing. When log(Price) is the dependent variable, we restrict our dataset to objects that attracted at least one bidder. Standard Errors are clustered at the auction level. The log-linear specification lends itself to the following interpretation of the main coefficient of interest in column (6), our preferred specification: *ceteris paribus*, a unit increase in the ratio of estimates increases the final expected price by approximately 10.2%.

Table 19: Linear Specification (2SLS)

7.4.5 Instrumenting Only the Ratio of Estimates.

	$\mathbb{1}(\# \text{ of Bidders} \geq 1)$			$\log(\text{Price})$		
	(1)	(2)	(3)	(4)	(5)	(6)
log(Min. Estimate)	0.015 (0.013)	0.045 (0.033)	-0.003 (0.014)	1.11*** (0.074)	1.34*** (0.207)	1.12*** (0.053)
log(Min. Estimate) square	-0.001 ⁺ (0.0009)	-0.003 ⁺ (0.002)	-0.0007 (0.0009)	-0.010* (0.005)	-0.024* (0.012)	-0.013*** (0.004)
Max./Min. Estimate	0.038 (0.056)	0.195 (0.155)	-0.008 (0.017)	0.151 (0.342)	1.39 (1.02)	0.306*** (0.077)
Max./Min. Estimate square	0.007 (0.013)	-0.003 (0.015)	0.002 (0.002)	-0.040 (0.059)	-0.139 (0.086)	-0.022*** (0.006)
Observations	57,201	57,201	57,201	52,765	52,765	52,765
R ²	0.439	0.440	0.478	0.770	0.773	0.791
Within R ²	-0.004	-0.012	0.0010	0.465	0.430	0.364
Seller FE	✓	✓	✓	✓	✓	✓
Expert FE		✓	✓		✓	✓
Auction FE			✓			✓

Standard Errors in parentheses.

+ : $p < 0.1$, * : $p < 0.05$, ** : $p < 0.01$, *** : $p < 0.001$.

Note: This table presents the regression output from an instrumental variable regression using the dummy variable equal to one if an object attracted at least one bidder as a dependent variable in columns (1) to (3) and using $\log(\text{Price})$ as a dependent variable in columns (4) to (6). Only the ratio of estimates and its square are considered endogenous and instrumented. Each observation is an object listing. When $\log(\text{Price})$ is the dependent variable, we restrict our dataset to objects that attracted at least one bidder. Standard Errors are clustered at the auction level. The log-linear specification lends itself to the following interpretation of the main coefficient of interest in column (6), our preferred specification: *ceteris paribus*, an increase from an initial ratio of estimates of 1 to a ratio of 2 increases the final expected price by $(0.524 - 0.284) \times 100 = 24\%$.

Table 20: $\log(\text{Min. Estimate})$ as an exogenous variable (2SLS).

7.4.6 Specifications with zero sales

	# of Bidders			Price		
	(1)	(2)	(3)	(4)	(5)	(6)
log(Min. Estimate)	0.180*** (0.043)	0.132** (0.043)	0.123* (0.048)	0.989*** (0.065)	0.998*** (0.061)	1.00*** (0.066)
log(Min. Estimate) square	-0.005+ (0.003)	-0.003 (0.003)	-0.003 (0.003)	-0.003 (0.004)	-0.004 (0.004)	-0.005 (0.004)
Max./Min. Estimate	0.176*** (0.042)	0.125** (0.041)	0.104* (0.042)	0.188* (0.087)	0.218** (0.081)	0.270*** (0.059)
Max./Min. Estimate square	-0.012** (0.004)	-0.008* (0.004)	-0.007+ (0.004)	-0.007 (0.007)	-0.010 (0.007)	-0.014* (0.006)
Observations	56,993	56,993	56,988	56,993	56,993	56,988
Squared Correlation	0.489	0.502	0.547	0.951	0.962	0.970
Pseudo R ²	0.253	0.258	0.278	0.922	0.925	0.931
Seller FE	✓	✓	✓	✓	✓	✓
Expert FE		✓	✓		✓	✓
Auction FE			✓			✓

+: $p < 0.1$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$; *SE clustered by Auction*

Standard Errors in parentheses.

+: $p < 0.1$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Note: This table presents the regression output from Poisson Pseudo Maximum Likelihood (PPML) regression using as a dependent variable the number of bidders (columns 1-3) and the final price (columns 4-6). Each observation is an object listing. Standard Errors are clustered at the auction level.

Table 21: Estimates with Poisson-Pseudo Maximum Likelihood (PPML)

7.5 Economic Mechanisms

7.5.1 Supply

	has Reserve Price (1)	is Sold (2)	log(Rank) (3)	is Promoted (4)	# of Bids (5)
log(Min. Estimate)	0.279*** (0.028)	-0.252*** (0.026)	-0.124 (0.102)	0.037 (0.023)	1.40* (0.641)
log(Min. Estimate) square	-0.014*** (0.002)	0.011*** (0.002)	-0.008 (0.007)	0.004** (0.002)	-0.039 (0.046)
Max./Min. Estimate	-0.126*** (0.023)	0.212*** (0.028)	-0.198** (0.065)	0.060*** (0.016)	1.64** (0.499)
Max./Min. Estimate square	0.009*** (0.002)	-0.014*** (0.002)	0.014* (0.007)	-0.004* (0.002)	-0.104* (0.046)
Observations	57,201	57,201	57,201	57,201	57,201
R ²	0.756	0.523	0.413	0.227	0.561
Within R ²	0.048	0.031	0.021	0.044	0.004
Seller FE	✓	✓	✓	✓	✓
Expert FE	✓	✓	✓	✓	✓
Auction FE	✓	✓	✓	✓	✓

Standard Errors in parentheses.

+: $p < 0.1$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Note: This table presents the regression output from a linear regression using in (1) a dummy equal to one if the object has a reserve price, in (2) a dummy equal to one if the object was ultimately sold, in (3) the log(Rank), in (4) a dummy equal to one if the object was promoted and in (5) the number of bids the object received as a dependent variable. Each observation is an object listing. Standard Errors are clustered at the auction level. The interpretation of the main coefficients of interest in column (1) is, *ceteris paribus*, that an increase of the ratio of estimates from 1 to 2 decreases the probability of the seller setting a reserve price by approximately 10% probability points. In column (2), the interpretation of the main coefficients of interest is that an increase of the ratio of estimates from 1 to 2 increases the probability to sell the object by approximately 17% probability points.

Table 22: The effects of experts' estimates on alternative outcomes (OLS)

Conclusion

The digital economy has brought significant benefits to society, but it has also raised concerns. Economic literature has identified potential market failures stemming from certain characteristics of digital markets. Public authorities, academics, and citizens have expressed worries that digital platforms may hold excessive market power in various industries. The wide array of pricing and non-pricing tools available to these firms makes them particularly agile, enabling them to create value in new areas of society, but can also diversify the ways in which they could potentially cause harm to consumers and society. The critical importance of platforms is undeniable, and for this reason, it is essential that public interventions create conditions that foster alignment between private and public incentives. In this thesis, we aim to contribute to the industrial organization literature by improving the understanding of platform strategies and their impact on competition and consumers.

In the first chapter, we examine how platforms' choice of business model can affect their incentives to invest in quality-improving innovation, and how these investments, in turn, influence their business model decisions. We build a theoretical model and consider a platform duopoly, where firms can decide choose their business model. Moreover, platforms can invest in quality-enhancing innovation for their consumers. Their incentives to do so depend on their ability to monetize their innovation. We find that business model differentiation can arise despite platforms being *ex-ante* identical, as it can allow platforms to charge monopoly prices in the advertising market. By comparing the equilibrium with the consumer surplus maximizing configuration, we identify a new source of distortion realized through business model decision. We emphasize that policy makers should take into account how they influence business model decisions as it might result in platforms users harm. This study has interesting policy implications. For instance, we argue that competition policy, or any policy that could influence the profitability of one business model over another, might seem like a good idea *a priori*. Indeed, enhancing platforms' ability to monetize their innovations can be beneficial to consumers. However, policymakers need to consider the impact of such a policy on platforms' business model decisions, as it could lead to a change in equilibrium and potentially harm consumers.

In the second chapter, we study the impact of Google's downstream position with YouTube on the contestability of the *adtech* stack and the competition for consumers

attention, building on a theoretical model. Our findings suggest that the integration of an *adtech* stack incumbent (e.g., Google) with a downstream display advertising platform (e.g., YouTube) can effectively and artificially raise barriers to entry. This is achieved in two ways. First, the acquisition of the display advertising platform can prevent any new entrant from competing for the newly acquired ad space, reducing entry profitability. Second, there is a collusive effect of integration that pushes the independent publisher to “make a deal with the devil”. An *adtech* stack incumbent can effectively use integration to leverage its downstream position, reducing market contestability as well as the level of competition for consumer attention. Ultimately, consumers are exposed to more ads, and integration is detrimental to them. We extend our analysis by considering that a regulator might want to impose advertising restrictions, similar to the European Union’s legislation on commercial breaks on TV. This study provides interesting policy insights as we examine a novel aspect of the concentration and vertical integration in the online display advertising industry. Adding to the concerns raised by Google’s position in the *adtech* stack, we argue that it may be able to leverage its downstream position and raise barriers to entry. However, restricting advertising levels might be a credible and efficient tool to limit these harmful effects of integration.

In the third chapter, we study platform-curated value estimations. On the online auction platform Catawiki, potential bidders can be provided with an estimation window for a specific product given by an in-house expert. We focus on assessing how this information provision from the platform can impact seller and buyer behaviors. They could provide useful information to potential bidders to help them assess their willingness to pay, but they might also distort this assessment in the interest of the platform. We leverage variations in the value of the maximum estimate relative to the minimum estimate and find sizable and statistically significant effects on seller and buyer behavior. Moreover, to account for potential omitted variable bias, we exploit quasi-random variations in the experts’ daily propensity to provide high estimates in the form of instrumental variables. We show that, despite being systematically overinflated, estimates benefit from user trust. Holding the value constant, a high ratio of the maximum to minimum estimate increases the final prices, generating larger platform revenues. Sellers also adjust their behavior by surprisingly decreasing their propensity to set a reserve price. As a result, they benefit from higher prominence on the platform and greater entry from bidders. Accounting for these effects, we still find sizable and significant effects of estimates on the final price, suggesting an impact on buyers’ valuation of the goods. This study provides valuable managerial and policy insights. It highlights the critical role of platform-provided information in enhancing market efficiency. In an auction context, reducing the cost of information acquisition for buyers leads to increased bidder participation, higher prices, and greater revenues. If an auction platform is listing a reasonable number of items, it may consider providing value estimates to help buyers better assess their willingness to

pay. However, a social planner might have legitimate concerns about potential biases in the value information provided by the platform, as it seeks to maximize its profits.

The three chapters of this thesis discuss pricing and non-pricing tools of digital platforms. They advocate that, to ensure consumer protection, there is a need for carefully designed regulation, that should build on past and future research.

Bibliography

- Aguiar, Luis, and Joel Waldfogel.** 2018. “Quality Predictability and the Welfare Benefits from New Products: Evidence from the Digitization of Recorded Music.” *Journal of Political Economy*, 126(2): 492–524.
- Aguiar, Luis, and Joel Waldfogel.** 2021. “Platforms, Power, and Promotion: Evidence from Spotify Playlists.” *The Journal of Industrial Economics*, 69(3): 653–691.
- Akerlof, George A, and Robert J Shiller.** 2015. *Phishing for Phools: The Economics of Manipulation and Deception*. Princeton University Press.
- Allouard, Hugo.** 2023. “Data Collection, Product Quality and Privacy Discrimination in Competitive Markets.” *Working Paper*.
- Ambrus, Attila, and Markus Reisinger.** 2006. “Exclusive vs Overlapping Viewers in Media Markets.”
- Anderson, Ashton, Lucas Maystre, Ian Anderson, Rishabh Mehrotra, and Mounia Lalmas.** 2020. “Algorithmic Effects on the Diversity of Consumption on Spotify.” *Proceedings of the Web Conference 2020*, 2155–2165.
- Anderson, Chris.** 2004. “The long tail.” *Wired magazine*, 12(10): 170–177.
- Anderson, Simon P., and Bruno Jullien.** 2015. “The Advertising-Financed Business Model in Two-Sided Media Markets.” In *Handbook of Media Economics*. Vol. 1, 41–90. Elsevier.
- Anderson, Simon P, and Özlem Bedre-Defolie.** 2021. “Hybrid platform model.”
- Anderson, Simon P, and Stephen Coate.** 2005. “Market provision of broadcasting: A welfare analysis.” *The review of Economic studies*, 72(4): 947–972.
- Anderson, Simon P., Øystein Foros, and Hans Jarle Kind.** 2018. “Competition for Advertisers and for Viewers in Media Markets.” *The Economic Journal*, 128(608): 34–54.

- Angrist, Joshua D, and Jörn-Steffen Pischke.** 2009. *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.
- Armstrong, Mark.** 2006. "Competition in two-sided markets." *The RAND journal of economics*, 37(3): 668–691.
- Armstrong, Mark, and Jidong Zhou.** 2022. "Consumer Information and the Limits to Competition." *American Economic Review*, 112(2): 534–77.
- Arthur, W. Brian.** 1989. "Competing Technologies, Increasing Returns, and Lock-In by Historical Events." *The Economic Journal*, 99(394): 116–131.
- Bakos, Yannis, and Hanna Halaburda.** 2020. "Platform competition with multihoming on both sides: Subsidize or not?" *Management Science*, 66(12): 5599–5607.
- Barsy, Laureen de, and Axel Gautier.** 2024. "Big Tech Acquisitions and Innovation: An Empirical Assessment."
- Ba, Sulin, and Paul A Pavlou.** 2002. "Evidence of the effect of trust building technology in electronic markets: Price premiums and buyer behavior." *MIS Quarterly*, 26(3): 243–268.
- Belleflamme, Paul, and Eric Toulemonde.** 2009. "Negative intra-group externalities in two-sided markets." *International Economic Review*, 50(1): 245–272.
- Belleflamme, Paul, and Martin Peitz.** 2018. "Inside the Engine Room of Digital Platforms: Reviews, Ratings, and Recommendations." *Aix-Marseille School of Economics*.
- Belleflamme, Paul, and Martin Peitz.** 2021. "Platforms: Definitions and Typology." *The Economics of Platforms: Concepts and Strategy*, 10–40. Cambridge University Press.
- Benlian, Alexander, Ryad Titah, and Thomas Hess.** 2012. "Differential effects of provider recommendations and consumer reviews in e-commerce transactions: An experimental study." *Journal of Management Information Systems*, 29(1): 237–272.
- Biglaiser, Gary, Emilio Calvano, and Jacques Crémer.** 2019. "Incumbency advantage and its value." *Journal of Economics & Management Strategy*, 28(1): 41–48.
- Bloch, Francis, and Axel Gautier.** 2017. "Strategic bypass deterrence." *Journal of Regulatory Economics*, 52: 189–210.
- Bobkova, Nina.** 2024. "Information choice in auctions." *American Economic Review*, 114(7): 1883–1915.

- Boudreau, KJ.** 2009. “Platform rules: Multi-sided platforms as regulators.” *Platform, Markets and Innovation/Edward Elgar*.
- Bourreau, Marc, and Germain Gaudin.** 2022a. “Streaming platform and strategic recommendation bias.” *Journal of Economics & Management Strategy*, 31(1): 25–47.
- Bourreau, Marc, and Germain Gaudin.** 2022b. “Streaming platform and strategic recommendation bias.” *Journal of Economics & Management Strategy*, 31(1): 25–47.
- Bourreau, Marc, Bruno Jullien, and Yassine Lefouili.** 2024. “Horizontal Mergers and Incremental Innovation.” *RAND Journal of Economics*, forthcoming.
- Brynjolfsson, Erik, Yu Jeffrey Hu, and Michael D Smith.** 2006. “From niches to riches: Anatomy of the long tail.” *MIT Sloan Management Review*, 47(4): 67.
- Cabral, Luis, and Ali Hortacsu.** 2010. “The Dynamics of Seller Reputation: Evidence from eBay.” *The journal of industrial economics*, 58(1): 54–78.
- Cai, Hongbin, Ginger Zhe Jin, Chong Liu, and Li-an Zhou.** 2014. “Seller Reputation: From Word-of-Mouth to Centralized Feedback.” *International Journal of Industrial Organization*, 34: 51–65.
- Caillaud, Bernard, and Bruno Jullien.** 2003. “Chicken & egg: Competition among intermediation service providers.” *RAND journal of Economics*, 309–328.
- Calvano, Emilio, and Michele Polo.** 2020. “Strategic Differentiation by Business Models: Free-To-Air and Pay-TV.” *The Economic Journal*, 130(625): 50–64.
- Calvano, Emilio, and Michele Polo.** 2021. “Market Power, Competition and Innovation in Digital Markets: A Survey.” *Antitrust in the Digital Economy*, 54: 100853.
- Casadesus-Masanell, Ramon, and Andres Hervas-Drane.** 2015. “Competing with Privacy.” *Management Science*, 61(1): 229–246.
- Casadesus-Masanell, Ramon, and Feng Zhu.** 2010. “Strategies to Fight Ad-Sponsored Rivals.” *Management Science*, 56(9): 1484–1499.
- Casadesus-Masanell, Ramon, and Gastón Llanes.** 2015. “Investment Incentives in Open-source and Proprietary Two-sided Platforms.” *Journal of Economics & Management Strategy*, 24(2): 306–324.
- Cecere, Grazia, Fabrice Le Guel, and Nicolas Soulié.** 2015. “Perceived internet privacy concerns on social networks in Europe.” *Technological Forecasting and Social Change*, 96: 277–287.

- Chen, Yongmin.** 2001. “On vertical mergers and their competitive effects.” *RAND Journal of Economics*, 667–685.
- Chen, Yuxin, and Song Yao.** 2017. “Sequential Search with Refinement: Model and Application with Click-Stream Data.” *Management Science*, 63(12): 4345–4365.
- Clemons, Eric K., Guodong “Gordon” Gao, and Lorin M. Hitt.** 2006. “When Online Reviews Meet Hyperdifferentiation: A Study of the Craft Beer Industry.” *Journal of Management Information Systems*, 23(2): 149–171.
- Competition and Markets Authority.** 2020. “Online platforms and digital advertising: A market study.” https://assets.publishing.service.gov.uk/media/5fa557668fa8f5788db46efc/Final_report_Digital_ALT_TEXT.pdf.
- Compte, Olivier, and Philippe Jehiel.** 2007. “Auctions and information acquisition: sealed bid or dynamic formats?” *The Rand Journal of Economics*, 38(2): 355–372.
- Crémer, Jacques, Yves-Alexandre de Montjoye, and Heike Schweitzer.** 2019. “Competition for the Digital Era, report for the European Commission (DG Competition).” Available at <https://awards.concurrences.com/IMG/pdf/5.competition.policy.for.the.digital.era.pdf>.
- Crémer, Jacques, Patrick Rey, and Jean Tirole.** 2000. “Connectivity in the Commercial Internet.” *The Journal of Industrial Economics*, 48(4): 433–472.
- Cunningham, Colleen, Florian Ederer, and Song Ma.** 2021. “Killer Acquisitions.” *Journal of Political Economy*, 129(3): 649–702.
- D’Annunzio, Anna.** 2017. “Vertical Integration in the TV Market: Exclusive Provision and Program Quality.” *International Journal of Industrial Organization*, 53: 114–144.
- de Cornière, Alexandre, and Greg Taylor.** 2014. “Integration and search engine bias.” *The RAND Journal of Economics*, 45(3): 576–597.
- de Cornière, Alexandre, and Romain De Nijs.** 2016. “Online advertising and privacy.” *The RAND Journal of Economics*, 47(1): 48–72.
- de Cornière, Alexandre.** 2016. “Search Advertising.” *American Economic Journal: Microeconomics*, 8(3): 156–188.
- De los Santos, Babur, and Sergei Koulayev.** 2017. “Optimizing Click-through in Online Rankings with Endogenous Search Refinement.” *Marketing Science*, 36(4): 542–564.

- Denicolò, Vincenzo, and Michele Polo.** 2018. “Duplicative Research, Mergers and Innovation.” *Economics Letters*, 166: 56–59.
- Dijk, Esmée, José L Moraga-González, and Evgenia Motchenkova.** 2021. “How Do Start-up Acquisitions Affect the Direction of Innovation?”
- Dijk, Esmée SR, José L Moraga-González, and Evgenia Motchenkova.** 2024. “Start-up acquisitions, strategic R&D, and the entrant’s and incumbent’s direction of innovation.” *Journal of Economics & Management Strategy*.
- Doganoglu, Toker, and Julian Wright.** 2006. “Multihoming and compatibility.” *International Journal of Industrial Organization*, 24(1): 45–67.
- Doleac, Jennifer L, and Luke CD Stein.** 2013. “The visible hand: Race and online market outcomes.” *The Economic Journal*, 123(572): F469–F492.
- Edelman, Benjamin, Michael Luca, and Dan Svirsky.** 2017. “Racial discrimination in the sharing economy: Evidence from a field experiment.” *American economic journal: applied economics*, 9(2): 1–22.
- Eisfeld, Luise.** 2023. “Entry and acquisitions in software markets.” *Unpublished Manuscript*.
- Etro, Federico.** 2021a. “Device-Funded vs Ad-Funded Platforms.” *International Journal of Industrial Organization*, 75: 102711.
- Etro, Federico.** 2021b. “Product selection in online marketplaces.” *Journal of Economics & Management Strategy*, 30(3): 614–637.
- Etro, Federico.** 2023. “e-Commerce platforms and self-preferencing.” *Journal of Economic Surveys*, , (12594).
- Fang, Lu, Yanyou Chen, Chiara Farronato, Zhe Yuan, and Yitong Wang.** 2024. “Platform Information Provision and Consumer Search: A Field Experiment.”
- Federico, Giulio, Gregor Langus, and Tommaso Valletti.** 2017. “A Simple Model of Mergers and Innovation.” *Economics Letters*, 157: 136–140.
- Filieri, Raffaele, and Fraser McLeay.** 2014. “E-WOM and Accommodation: An Analysis of the Factors That Influence Travelers’ Adoption of Information from Online Reviews.” *Journal of Travel Research*, 53(1): 44–57.
- Foroughifar, Mohsen, and Nitin Mehta.** 2024. “The Challenges of Deploying an Algorithmic Pricing Tool: Evidence from Airbnb.” *SSRN Electronic Journal*.

- Fradkin, Andrey, Elena Grewal, Dave Holtz, and Matthew Pearson.** 2015. “Bias and Reciprocity in Online Reviews: Evidence From Field Experiments on Airbnb.” *EC*, 15: 15–19.
- Furman, Jason, Diane Coyle, Amelia Fletcher, Derek McAuley, and Philip Marsden.** 2019. “Unlocking digital competition: Report of the digital competition expert panel.” *UK government publication, HM Treasury*, 27.
- Gautier, Axel, and Joe Lamesch.** 2021. “Mergers in the digital economy.” *Information Economics and Policy*, 54: 100890.
- Ghose, Anindya, Panagiotis G. Ipeirotis, and Beibei Li.** 2012. “Designing Ranking Systems for Hotels on Travel Search Engines by Mining User-Generated and Crowd-sourced Content.” *Marketing Science*, 31(3): 493–520.
- Ghose, Anindya, Panagiotis G. Ipeirotis, and Beibei Li.** 2014. “Examining the Impact of Ranking on Consumer Behavior and Search Engine Revenue.” *Management Science*, 60(7): 1632–1654.
- Goldfarb, Avi, and Catherine Tucker.** 2019. “Digital Economics.” *Journal of Economic Literature*, 57(1): 3–43.
- Hagiu, Andrei, and Julian Wright.** 2015. “Multi-sided platforms.” *International Journal of Industrial Organization*, 43: 162–174.
- Hagiu, Andrei, and Julian Wright.** 2023. “Data-enabled learning, network effects, and competitive advantage.” *The RAND Journal of Economics*, 54(4): 638–667.
- Hagiu, Andrei, Tat-How Teh, and Julian Wright.** 2022a. “Should platforms be allowed to sell on their own marketplaces?” *The RAND Journal of Economics*, 53(2): 297–327.
- Hagiu, Andrei, Tat-How Teh, and Julian Wright.** 2022b. “Should platforms be allowed to sell on their own marketplaces?” *The RAND Journal of Economics*, 53(2): 297–327.
- Hagiu, Andrei, Tat-How Teh, and Julian Wright.** 2023. “Private Labels and Platform Self-Preferencing.” *Working Paper*.
- Halaburda, Hanna, and Yaron Yehezkel.** 2019. “Focality advantage in platform competition.” *Journal of Economics & Management Strategy*, 28(1): 49–59.
- Halaburda, Hanna, Bruno Jullien, and Yaron Yehezkel.** 2020. “Dynamic competition with network externalities: how history matters.” *The RAND Journal of Economics*, 51(1): 3–31.

- Hann, Il-Horn, and Christian Terwiesch.** 2003. “Measuring the frictional costs of online transactions: The case of a name-your-own-price channel.” *Management Science*, 49(11): 1563–1579.
- Hansen, Christian, Rishabh Mehrotra, Casper Hansen, Brian Brost, Lucas Maystre, and Mounia Lalmas.** 2021. “Shifting Consumption towards Diverse Content on Music Streaming Platforms.” 238–246.
- Hart, Oliver, and Jean Tirole.** 1990. “Vertical Integration and Market Foreclosure.” *Brookings Papers on Economic Activity. Microeconomics*, 1990: 205–286.
- Hałaburda, Hanna, and Yaron Yehezkel.** 2016. “The Role of Coordination Bias in Platform Competition.” *Journal of Economics & Management Strategy*, 25(2): 274–312.
- Holtz, David, Ben Carterette, Praveen Chandar, Zahra Nazari, Henriette Cramer, and Sinan Aral.** 2020. “The Engagement-Diversity Connection: Evidence from a Field Experiment on Spotify.” 75–76.
- Horton, John, and Joseph Golden.** 2015. “Reputation Inflation: Evidence from an Online Labor Market.” *Work. Pap., NYU*, 1.
- Hotelling, Harold.** 1929. “Stability in Competition.” *The Economic Journal*, 39(153): 41–57.
- Hu, Nan, Jie Zhang, and Paul A Pavlou.** 2009. “Overcoming the J-shaped distribution of product reviews.” *Communications of the ACM*, 52(10): 144–147.
- Hunold, Matthias, Reinhold Kesler, and Ulrich Laitenberger.** 2020*a*. “Rankings of online travel agents, channel pricing, and consumer protection.” *Marketing Science*, 39(1): 92–116.
- Hunold, Matthias, Reinhold Kesler, and Ulrich Laitenberger.** 2020*b*. “Rankings of Online Travel Agents, Channel Pricing, and Consumer Protection.” *Mark. Sci.*, 39: 92–116.
- Hunold, Matthias, Ulrich Laitenberger, and Guillaume Thébaudin.** 2022. “Bye-Box: An Analysis of Non-Promotion on the Amazon Marketplace.” *Working Paper*.
- Janssen, Maarten, Thomas Jungbauer, Marcel Preuss, and Cole Williams.** 2023. “Search Platforms: Big Data and Sponsored Positions.” *CEPR Discussion Papers*, (18639).
- Jeitschko, Thomas D, and Mark J Tremblay.** 2020. “Platform competition with endogenous homing.” *International Economic Review*, 61(3): 1281–1305.

- Jin, Ginger Zhe, and Andrew Kato.** 2006. “Price, Quality, and Reputation: Evidence from an Online Field Experiment.” *The RAND Journal of Economics*, 37(4): 983–1005.
- Johansen, Bjørn Olav, and Thibaud Vergé.** 2017. “Platform price parity clauses with direct sales.” *University of Bergen*.
- Jullien, Bruno, and Alessandro Pavan.** 2019. “Information Management and Pricing in Platform Markets.” *The Review of Economic Studies*, 86(4 (309)): pp. 1666–1703.
- Jullien, Bruno, and Matthieu Bouvard.** 2023. “Fair cost sharing: big tech vs telcos.” TSE Working Paper, no 1376.
- Kagel, John H., and Dan Levin.** 1986. “The Winner’s Curse and Public Information in Common Value Auctions.” *American Economic Review*, 76(5): 894–920.
- Kagel, John H, and Dan Levin.** 1993. “Independent private value auctions: Bidder behaviour in first-, second-and third-price auctions with varying numbers of bidders.” *The Economic Journal*, 103(419): 868–879.
- Kagel, John H, Ronald M Harstad, Dan Levin, et al.** 1987. “Information impact and allocation rules in auctions with affiliated private values: A laboratory study.” *Econometrica*, 55(6): 1275–1304.
- Karle, Heiko, Martin Peitz, and Markus Reisinger.** 2020. “Segmentation versus agglomeration: Competition between platforms with competitive sellers.” *Journal of Political Economy*, 128(6): 2329–2374.
- Katz, Michael L., and Carl Shapiro.** 1985. “Network Externalities, Competition, and Compatibility.” *The American Economic Review*, 75(3): 424–440.
- Kirpalani, Rishabh, and Thomas Philippon.** 2020. “Data Sharing and Market Power with Two-Sided Platforms.”
- Klein, Tobias J., Christian Lambertz, and Konrad O. Stahl.** 2013. “Adverse Selection and Moral Hazard in Anonymous Markets.” *ZEW-Centre for European Economic Research Discussion Paper*, , (13-050).
- Kling, Jeffrey R.** 2006. “Incarceration Length, Employment, and Earnings.” *American Economic Review*, 96(3): 863–876.
- Lambrecht, Anja, and Catherine E Tucker.** 2015. “Can big data protect a firm from competition?” *Available at SSRN 2705530*.
- Lee, Kwok Hao, and Leon Musolff.** 2021. “Entry into two-sided markets shaped by platform-guided search.” *Working Paper*.

- Lefez, Willy.** 2022. “Price Recommendations and the Value of Data.” *SSRN Electronic Journal*.
- Levin, Jonathan.** 2001. “Information and the Market for Lemons.” *RAND Journal of Economics*, 657–666.
- Li, Guo, Lin Tian, and Hong Zheng.** 2021. “Information Sharing in an On-line Marketplace with Co-opetitive Sellers.” *Production and Operations Management*, 30(10): 3713–3734.
- Liu, Yi, Pinar Yildirim, and Z John Zhang.** 2022. “Implications of revenue models and technology for content moderation strategies.” *Marketing Science*, 41(4): 831–847.
- Livingston, Jeffrey A.** 2005. “How Valuable Is a Good Reputation? A Sample Selection Model of Internet Auctions.” *Review of Economics and Statistics*, 87(3): 453–465.
- Long, Fei, and Wilfred Amaldoss.** 2024. “Self-preferencing in e-commerce marketplaces: The role of sponsored advertising and private labels.” *Marketing Science*.
- Luca, Michael.** 2017. “Designing online marketplaces: Trust and reputation mechanisms.” *Innovation Policy and the Economy*, 17(1): 77–93.
- Luca, Michael, and Georgios Zervas.** 2016. “Fake It Till You Make It: Reputation, Competition, and Yelp Review Fraud.” *Management Science*, 62(12): 3412–3427.
- Madio, Leonardo, and Martin Quinn.** 2024. “Content moderation and advertising in social media platforms.” *Journal of Economics & Management Strategy*.
- Madsen, Erik, and Nikhil Vellodi.** 2023. “Insider imitation.” *Forthcoming, Journal of Political Economy 2023*.
- Magnani, Marco, and Federico Navarra.** 2023. “Information provision in hybrid platforms.” *Available at SSRN 4453550*.
- Malika, Korganbekova.** 2023. “Regulating data usage by dual platforms.” *Working Paper*.
- Manant, Matthieu, Serge Pajak, and Nicolas Soulié.** 2019. “Can social media lead to labor market discrimination? Evidence from a field experiment.” *Journal of Economics & Management Strategy*, 28(2): 225–246.
- Mantovani, Andrea, Claudio A Piga, and Carlo Reggiani.** 2021. “Online platform price parity clauses: Evidence from the EU Booking.com case.” *European Economic Review*, 131: 103625.

- Marra, Marleen.** 2021. “Estimating an auction platform game with two-sided entry.” Working Paper, Sciences Po.[507].
- Matthews, Steven.** 1977. “Information acquisition in competitive bidding processes.” *Mimeographed, California Institute of Technology, Pasadena, CA.*
- Mayzlin, Dina, Yaniv Dover, and Judith Chevalier.** 2014. “Promotional Reviews: An Empirical Investigation of Online Review Manipulation.” *The American Economic Review*, 104(8): 2421–2455.
- McDonald, Cynthia G., and V. Carlos Slawson Jr.** 2002. “Reputation in an Internet Auction Market.” *Economic inquiry*, 40(4): 633–650.
- Mermelstein, Ben, Volker Nocke, Mark A. Satterthwaite, and Michael D. Whinston.** 2020. “Internal versus External Growth in Industries with Scale Economies: A Computational Model of Optimal Merger Policy.” *Journal of Political Economy*, 128(1): 301–341.
- Milgrom, Paul R.** 1981. “Rational expectations, information acquisition, and competitive bidding.” *Econometrica: Journal of the Econometric Society*, 921–943.
- Milgrom, Paul R, and Robert J Weber.** 1982. “A theory of auctions and competitive bidding.” *Econometrica: Journal of the Econometric Society*, 1089–1122.
- Mudambi, Susan M, and David Schuff.** 2010. “What makes a helpful online review? A study of customer reviews on Amazon.com.” *MIS Quarterly*, 34(1): 185–200.
- Nagaraj, Abhishek, and Aruna Ranganathan.** 2022. “Singing Your Own Praises: Digital Cultural Production and Gender Inequality.” Working paper, University of California-Berkeley, Haas School of Business.
- Navarra, Federico, et al.** 2023. “Digital platforms’ strategies: price parity, information provision and data sharing.”
- Nosko, Chris, and Steven Tadelis.** 2015. “The Limits of Reputation in Platform Markets: An Empirical Analysis and Field Experiment.” National Bureau of Economic Research.
- Ordober, Janusz A, Garth Saloner, and Steven C Salop.** 1990*a*. “Equilibrium Vertical Foreclosure.” *The American Economic Review*, 127–142.
- Ordober, Janusz A, Garth Saloner, and Steven C Salop.** 1990*b*. “Equilibrium vertical foreclosure.” *The American Economic Review*, 127–142.

- Pape, Louis-Daniel, and Michelangelo Rossi.** 2024. “Is Competition Only One Click Away? The Digital Markets Act Impact on Google Maps.” CESifo CESifo Working Paper 11226.
- Peitz, Martin, and Markus Reisinger.** 2015. “The economics of internet media.” In *Handbook of media economics*. Vol. 1, 445–530. Elsevier.
- Persico, Nicola.** 2000. “Information acquisition in auctions.” *Econometrica*, 68(1): 135–148.
- Piolatto, Amedeo, and Florian Schuett.** 2022. “Information vs Competition: How Platform Design Affects Profits and Surplus.” Barcelona School of Economics Working Papers 1325.
- Rasmusen, Eric.** 1988. “Entry for Buyout.” *The Journal of Industrial Economics*, 36(3): 281–299.
- Reimers, Imke, and Joel Waldfogel.** 2023. “A Framework for Detection, Measurement, and Welfare Analysis of Platform Bias.” National Bureau of Economic Research.
- Resnick, Paul, Richard Zeckhauser, John Swanson, and Kate Lockwood.** 2006. “The Value of Reputation on eBay: A Controlled Experiment.” *Experimental economics*, 9: 79–101.
- Rey, Patrick, and Jean Tirole.** 2007. “A primer on foreclosure.” *Handbook of industrial organization*, 3: 2145–2220.
- Riordan, Michael H.** 2005. “Competitive effects of vertical integration.”
- Rochet, Jean-Charles, and Jean Tirole.** 2003. “Platform competition in two-sided markets.” *Journal of the european economic association*, 1(4): 990–1029.
- Rochet, Jean-Charles, and Jean Tirole.** 2006. “Two-sided markets: a progress report.” *The RAND journal of economics*, 37(3): 645–667.
- Rohlfs, Jeffrey.** 1974. “A theory of interdependent demand for a communications service.” *The Bell journal of economics and management science*, 16–37.
- Rysman, Marc.** 2009. “The economics of two-sided markets.” *Journal of economic perspectives*, 23(3): 125–143.
- Salinger, Michael A.** 1988. “Vertical mergers and market foreclosure.” *The Quarterly Journal of Economics*, 103(2): 345–356.

- Scott Morton, Fiona, Pascal Bouvier, Ariel Ezrachi, Bruno Jullien, Roberta Katz, Gene Kimmelman, Douglas Melamed, and Jamie Morgenstern.** 2019. “Stigler Committee on Digital Platforms: Final Report.” Stigler Center for the Study of the Economy and the State, University of Chicago Booth School of Business. Available at <https://research.chicagobooth.edu/stigler/media/news/committee-on-digitalplatforms-final-report>.
- Shapiro, Carl.** 1999. *Information rules: A strategic guide to the network economy*. Harvard Business School Press.
- Spengler, Joseph J.** 1950. “Vertical integration and antitrust policy.” *Journal of political economy*, 58(4): 347–352.
- Tadelis, Steven.** 2023. “Reputation, Feedback, and Trust in Online Platforms.” *Reengineering the Sharing Economy: Design, Policy, and Regulation*, 62.
- Teh, Tat-How.** 2022. “Platform governance.” *American Economic Journal: Microeconomics*, 14(3): 213–254.
- Teh, Tat-How, and Julian Wright.** 2022. “Intermediation and steering: Competition in prices and commissions.” *American Economic Journal: Microeconomics*, 14(2): 281–321.
- Varian, Hal R, Joseph Farrell, and Carl Shapiro.** 2004. *The economics of information technology: An introduction*. Cambridge University Press.
- Varma, Gopal Das.** 2002. “Standard auctions with identity-dependent externalities.” *RAND Journal of Economics*, 689–708.
- Waldfogel, Joel.** 2024. “Amazon Self-preferencing in the Shadow of the Digital Markets Act.” National Bureau of Economic Research.
- Wang, Ruitong, and Ye Qiu.** 2024. “Dual Role and Product Featuring Strategy of Digital Platform.” *Marketing Science*.
- Weeds, Helen.** 2013. “Programme Quality in Subscription and Advertising-Funded Television.” working paper.
- Zennyo, Yusuke.** 2022. “Platform encroachment and own-content bias.” *The Journal of Industrial Economics*, 70(3): 684–710.
- Zervas, Georgios, Davide Proserpio, and John W. Byers.** 2021. “A First Look at Online Reputation on Airbnb, Where Every Stay Is above Average.” *Marketing Letters*, 32: 1–16.

Résumé en français

L'émergence de l'économie numérique a généré des bénéfices significatifs pour la société, tout en soulevant de nombreuses inquiétudes. La littérature académique en sciences économiques a mis en évidence plusieurs défaillances de marché potentielles, directement liées à certaines caractéristiques des industries numériques. À plusieurs reprises, les autorités publiques, le monde académique et la société civile ont exprimé leurs préoccupations quant au pouvoir de marché potentiellement excessif dont pourraient bénéficier les plateformes numériques dans de nombreux secteurs.

La grande diversité des outils tarifaires et non tarifaires à leur disposition confère à ces entreprises une forme d'agilité, leur permettant de créer de la valeur dans de nouveaux domaines, mais aussi de diversifier les pratiques susceptibles de nuire à leurs concurrents et aux consommateurs. Les plateformes occupent une place singulière dans nos sociétés ; c'est précisément pour cette raison qu'il est essentiel que les interventions des pouvoirs publics favorisent un alignement entre intérêts privés et publics.

Cette thèse vise à enrichir la littérature théorique et empirique en économie industrielle en approfondissant la compréhension des stratégies employées par les plateformes numériques et leur impact sur la concurrence ainsi que sur le bien-être des consommateurs.

Dans le premier chapitre, coécrit avec Marie-Laure Allain et Marc Bourreau, nous étudions comment le choix du modèle d'affaires d'une plateforme peut influencer son incitation à innover. Nous modélisons un marché en duopole où les plateformes peuvent choisir leur modèle d'affaires : être financées par la publicité ou par la vente d'abonnements ou de produits. Par ailleurs, elles peuvent investir pour améliorer la qualité de leur produit ou service.

Les incitations des firmes à investir dépendent de leur capacité à monétiser leurs innovations. Nous montrons qu'à l'équilibre, des firmes pourtant identiques ex ante peuvent adopter des modèles d'affaires différents. Ce résultat s'explique par le fait que cette différenciation leur permet de pratiquer des prix monopolistiques sur le marché publicitaire. La comparaison entre l'équilibre issu des choix des plateformes et la configuration maximisant le surplus des consommateurs révèle que le choix du modèle d'affaires peut être une source de distorsion.

Nos résultats soulignent que les législateurs devraient prendre en compte l'impact de leurs décisions sur le choix du modèle d'affaires des plateformes, car elles pourraient, in fine, nuire aux consommateurs. Par exemple, nous analysons des politiques visant à influencer la rentabilité d'un modèle d'affaires pour stimuler l'innovation. Si de telles politiques semblent a priori bénéfiques, elles peuvent avoir des effets indésirables. En effet, améliorer la capacité d'une entreprise à monétiser ses innovations peut renforcer ses incitations à investir et bénéficier aux consommateurs. Toutefois, une telle politique peut aussi modifier l'équilibre des choix de modèles d'affaires et, in fine, réduire l'effort d'innovation global, au détriment des consommateurs.

Dans le deuxième chapitre, je propose une analyse de l'effet de l'intégration verticale entre Google et YouTube sur la contestabilité du marché de l'intermédiation publicitaire en ligne (l'*adtech*) et sur la concurrence pour l'attention des consommateurs, à l'aide d'un modèle théorique.

Mes résultats suggèrent que l'intégration d'une firme en place dans l'*adtech* (par exemple, Google) avec une plateforme financée par la publicité et non liée aux recherches (ou éditeur) en aval (par exemple, YouTube) peut artificiellement accroître les barrières à l'entrée. Deux facteurs expliquent ce phénomène. Premièrement, l'acquisition d'un éditeur par la firme en place peut empêcher un nouvel entrant de proposer des services d'intermédiation publicitaire sur les espaces publicitaires de l'éditeur intégré, réduisant ainsi la rentabilité de l'entrée. Deuxièmement, l'intégration verticale a des effets "collusifs", incitant les éditeurs indépendants à conclure un "pacte avec le diable" en utilisant les services d'intermédiation de leurs concurrents en échange d'une concurrence adoucie sur le marché de l'attention des consommateurs. Une firme en place dans l'*adtech* peut donc exploiter l'intégration avec un éditeur comme un levier pour réduire la contestabilité du marché dans lequel elle opère et limiter la concurrence pour l'attention des consommateurs, les exposant ainsi à des niveaux de publicité plus élevés.

J'explore également une extension de l'analyse en examinant la possibilité, pour un régulateur, d'imposer des restrictions publicitaires aux éditeurs en ligne, dans l'esprit des réglementations européennes sur la télévision. Je montre que ce type de régulation constitue un outil comportemental efficace et relativement simple pour atténuer les effets négatifs et anticoncurrentiels de l'intégration entre un fournisseur de services d'intermédiation publicitaire en ligne et un éditeur.

Dans le troisième chapitre, coécrit avec Louis Pape, nous analysons la fourniture d'informations sur la valeur d'un bien par une plateforme d'enchères en ligne. Sur Catawiki, les participants à une enchère peuvent consulter une fourchette d'estimation de la valeur du bien mis en vente, fournie par un expert employé par la plateforme. Nous cherchons à quantifier dans quelle mesure cette information influence le comportement des vendeurs et des acheteurs. D'un côté, l'expert pourrait fournir des indications utiles

aux consommateurs pour mieux estimer leur disposition à payer. De l'autre, il pourrait aussi biaiser l'information et influencer la prise de décision des enchérisseurs dans l'intérêt de la plateforme, son employeur.

Nous exploitons les variations entre la borne haute et la borne basse de l'estimation et trouvons des effets non négligeables et statistiquement significatifs sur le comportement des acheteurs et des vendeurs. Pour contrôler un éventuel biais d'omission de variable, nous utilisons une approche par variables instrumentales, en nous appuyant sur des fluctuations quasi-aléatoires du comportement des experts et de leur propension à donner des estimations plus ou moins élevées d'un jour à l'autre. Nous montrons que, bien que les estimations des experts soient régulièrement surestimées, elles bénéficient d'un certain degré de confiance de la part des utilisateurs. À valeur de bien constante, une augmentation du ratio entre la borne haute et la borne basse conduit à une hausse des sommes enchéries, augmentant ainsi les profits de la plateforme. Les vendeurs adaptent également leur comportement en renonçant plus fréquemment à fixer un prix de réserve. Ils bénéficient ainsi d'une meilleure exposition, attirant ainsi davantage de participants potentiels sur leur page produit. Enfin, en prenant en compte les effets sur la demande, nous constatons que les estimations des experts ont toujours un impact significatif sur les prix, ce qui suggère qu'elles constituent un outil efficace pour accroître la disposition à payer des consommateurs, indépendamment de la valeur intrinsèque du produit proposé.

Les trois chapitres de cette thèse étudient des outils tarifaires et non-tarifaires à disposition des plateformes numériques. Ils mettent en évidence que, pour garantir une protection efficace des consommateurs face à de potentielles pratiques néfastes des plateformes, les législateurs doivent faire preuve de prudence dans la conception et l'application de politiques de régulation. Il est notamment essentiel qu'ils s'appuient sur les travaux académiques existants et futurs.

Titre : Stratégies et Régulation des Plateformes Numériques : Essais en Économie Industrielle

Mots clés : Économie Industrielle, Économie Numérique, Plateformes Numériques, Innovation, Publicité en Ligne, Fourniture d'Information

Résumé : Cette thèse traite du pouvoir de marché des entreprises numériques. Elle a pour but de fournir des éléments de réflexion aux législateurs, en leur permettant de mieux comprendre les stratégies des plateformes numériques et l'impact qu'elles peuvent avoir sur leur marché et ses participants.

Dans le premier chapitre, nous proposons une analyse théorique du choix de modèle d'affaires des plateformes et de l'impact de ce dernier sur l'innovation. À l'équilibre, les plateformes peuvent choisir d'adopter des modèles d'affaires différents, ce qui leur permet d'être potentiellement plus innovantes grâce à un effet *Schumpéterien* de la différenciation par le modèle d'affaires. Nos travaux montrent que le choix du modèle d'affaires peut être une source de distorsion, qui devrait être prise en compte par les législateurs lors de la conception de politiques cherchant à stimuler l'innovation.

Dans le second chapitre, je réalise une étude théorique de la contestabilité du marché de l'intermédiation publicitaire en ligne (*adtech*). Ses résultats suggèrent que l'intégration verticale entre une firme établie dans l'*adtech* et une plateforme en aval offrant de l'espace publicitaire (par ex.

Google et YouTube) peut permettre à la firme en place de réduire la contestabilité de l'*adtech*. J'étudie l'efficacité d'une politique consistant à imposer des restrictions publicitaires, dans l'esprit des réglementations européennes sur les pauses publicitaires à la télévision. Je montre qu'elles pourraient représenter un outil efficace pour améliorer la protection du consommateur face à une exposition excessive à la publicité, mais aussi pour limiter les effets négatifs de l'intégration verticale.

Dans le troisième chapitre, nous étudions empiriquement l'effet de la fourniture d'informations relatives à la valeur d'un bien par des plateformes d'enchères en ligne. Nos résultats indiquent que, à valeur intrinsèque constante, de plus hautes estimations de valeur affichées sur la page d'un bien augmentent la disposition à payer des acheteurs. Nous montrons que les estimations que la plateforme peut fournir influencent les consommateurs, bien qu'elles semblent régulièrement surévaluées. Cette étude met en évidence l'impact des informations mises à disposition par les plateformes sur l'efficacité du marché au sein duquel elles opèrent.

Title : Digital Platforms' Strategies and Regulation: Essays in Industrial Organization

Keywords : Industrial Organization, Digital Economics, Digital Platforms, Innovation, Online Advertising, Information Provision

Abstract : This thesis focuses on market power in digital markets. It aims at providing insights to policy makers, by allowing them to understand digital platforms' strategies and their impact on market outcomes.

The first chapter theoretically examines platforms' business model decisions, and their impact on innovation. In equilibrium, platforms can differentiate in business model, potentially allowing them to innovate more thanks to a Schumpeterian effect of business model differentiation. We identify that business model can be a source of distortion, and that policy makers should take it into account in attempting to design innovation stimulating policies.

The second chapter theoretically studies the *adtech* stack contestability. Its results indicate that vertical integration between an incumbent *adtech* stack with a downstream display advertising platforms (e.g.

Google and YouTube) is a way to successfully reduce *adtech* contestability. I discuss the efficiency of online advertising restrictions, in the spirit of European Union TV regulations, in tackling issues related to such integration and protecting end users from excessive exposure to online advertising.

The third chapter empirically inspects the effect of products value assessment information provision by online auction platforms. Our findings indicate that, holding intrinsic object value constant, higher expert estimates increase buyers valuation for the good. Despite potential conflicts of interest stemming from the platform's dual role as matchmaker and advisor, our results show that expert estimates are influential even when potentially overinflated. This study underscores the critical role of platform-provided information in enhancing market efficiency.