Regulation and competition policy of the digital economy : essays in industrial organization

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Yassine Lefouili Professeur, Ecole d'économie de Toulouse	Président
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Mais pourquoi se faire économiste ? Que diable allait-il faire dans cette galère ?

Correspondance de l'abbé Galiani
avec Mme d'Épinay
(à propos de Turgot).

Ayant reconnu le fait que les industries sont différentes les unes des autres et qu'elles évoluent rapidement, les chercheurs en économie industrielle ont patiemment constitué un corpus de connaissances qui a aidé les régulateurs à mieux comprendre le pouvoir de marché et les effets des interventions politiques, et les entreprises à formuler leurs stratégies. Ils ont ainsi contribué à bâtir un monde meilleur, la mission première de l'économiste.

Jean Tirole
Discours du Nobel

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Introduction

By simply transforming the representation of information into bits, digital technologies have led to a profound transformation of human societies, reshaping the interaction between individuals, businesses and governments. The coronavirus pandemic made this particularly striking. While the entire planet was deprived of physical contact, digital activities allowed humanity to stay connected.[1] People have used digital tools to live, work, learn and shop online. Consequently, Internet traffic increased by 60% in OECD countries shortly after the virus emerged.[2] The crisis has demonstrated the potential of digital technologies and accelerated the digital transition.[3] In particular, artificial intelligence (AI) has been used to learn more about the virus and speed up the search for a vaccine.

The pandemic also emphasises the various challenges of the digital world. Scams and phishing campaigns have proliferated as malicious actors took advantage of the massive shift to online activity,[4] whereas the diffusion of fake news has been facilitated by social media.[5]

In this thesis, we address two specific challenges for the digital economy: AI explainability and the contestability of digital markets.

AI explainability. Lockdowns, social distancing and workers' vulnerability to the virus have given further stimulus to automation and the use of artificial intelligence. For instance, many firms turned to AI-based hiring tools to manage the applications received during the pandemic. AI allows to predict the performance of a candidate for a given job, based on their behaviour in an interview – their gestures, pose, tone and cadence – and the content of their answers. This process produces an employability score that employers can use to decide who moves forward in the application process.[6] However, automated hiring machines, and more generally AI technologies, cannot explain their decisions in human terms. This has raised concerns that these hiring tools may

[1] Several papers study the inequality in people's ability to self-isolate (e.g., Chiou and Tucker (2020)).

[2] OECD, *Keeping the Internet Up and Running in Times of Crisis*, 2020. See also, OECD, Digital Economy Outlook Supplement, *Digital Transformation in the Age of Covid-19*, 2020.

[3] Firms have invested in boosting their digital transition (see e.g., McKinsey report, *How Covid-19 has pushed companies over the technology tipping point*, October 2020).

[4] See, e.g., Interpol report, *COVID-19 Cybercrime Analysis Report*, August 2020.

[5] As previous studies observed (e.g., Vosoughi et al. (2018)), fake news spread much further, faster, deeper, and wider than the truth. See Singh and Singh (2021) for a broader view on this subject.

[6] According to a survey by Workato, the automated recruitment process increasing by more than six-fold (547%) compared to its previous 2020's report (*Workato, Work Automation Index*, 2021).

produce biased results – unintentionally favouring men or people from specific socio-economic backgrounds, for example. In particular, a complaint was filed against the AI recruitment company HireVue for the potential bias generated by its technology.[7] The firm claims that it did not do anything illegal. But, partly in response to the criticism, HireVue announced that it had stopped using a candidate's facial expressions in its video interviews.

This example shows that the lack of explainability of the technology makes it hard to detect or determine whether harm (here, bias or discrimination) has occurred.

In Section 1 of this introduction, I discuss how the emergence of AI technologies can make regulatory design and enforcement more difficult, which is then formalised in Chapter 1 of the thesis.

Contestability of digital markets. The pandemic crisis has also raised concerns about market consolidation, as start-ups and small and medium enterprises struggle to stay afloat, while large big-tech platforms exert increasing influence over the digital economy.

Big-tech firms rely on significant returns to scale, economies of scope or network effects between different types of users to secure their dominant position. This can lead to strong, dominant positions that are no longer contestable by entrants. Dominant firms may also deter competition from potential rivals by engaging in anticompetitive behaviour. The relevant questions are then whether competition can emerge and persist in the digital economy, whether the position of the big-tech platforms is contestable, and whether regulation is necessary.

In Section 2 of the introduction, I examine why the emergence of dominant platforms makes the design and enforcement of regulation more difficult. In the thesis, I investigate two possible remedies, coopetition in Chapter 2 and interoperability in Chapter 3.

1 Regulatory informational challenges in the digital economy

Search, replication, transportation, tracking, and verification costs are lower in the digital than in the physical world (Goldfarb and Tucker; 2019). As a consequence, an increasing number of activities are performed digitally. In 2019, the size of the digital

[7] In 2019, Electronic Privacy Information Center, a non-profit organisation, filed a complaint with the Federal Trade Commission against HireVue's, alleging that its use of AI to evaluate video interviews of job applicants constituted "unfair and deceptive trade practices".

economy was estimated between 4.5% to 15.5% of global GDP, with a growing trend.[8] Digital innovations make it increasingly easy to collect, store and analyse data from online activities, allowing firms to develop and improve their products, gain more precise insights into consumers' needs, and develop new business models and decision-making methods.

At the same time, as the transposition of traditional decision-making methods into the digital world has made it possible to automate processes, new methods have been developed based on massive data, generally referred to as artificial intelligence (AI). A possible definition of artificial intelligence is the one proposed by Acemoglu and Restrepo (2020): "[Artificial Intelligence] refers to the study and development of 'intelligent (machine) agents', which are machines, software, or algorithms that act intelligently by recognising and responding to their environment." AI provide better predictions, assist decisions, optimise processes, and enable personalised services.[9]

AI adoption. Almost all digital platforms use AI, and its adoption continues to increase in all industries.[10] AI has been adopted by more than half of the organisations surveyed by McKinsey in 2020.[11] Some government agencies have also started relying on AI, especially in the criminal justice system and customs and immigration control.[12]

AI is likely to have transformative effects on the economy, society and politics. Like the steam engine, electrification, and the Internet, AI can be viewed as a general-purpose technology (Agrawal et al. (2019)) used to develop a variety of new products, services, and production techniques (Acemoglu (2021)).[13] Thus, AI is likely to impact a wide range of sectors, and the most emblematic one is the transportation industry in which AI allows the development of autonomous vehicles.[14] But many other sectors

[8]Estimation in the Proposal for a regulation on contestable and fair markets in the digital sector.

[9]See (De Corniere and Taylor; 2020). Schaefer et al. (2018) show that more data can provide more relevant research results. Bajari et al. (2019) shows that it predict future demand more accurately.

[10]Crawford et al. (2019).

[11]The organisations have adopted AI in at least one function (e.g., service operations, product or service development, and marketing and sales). Data are from an online survey that garnered responses from 2,360 participants representing the full range of regions, industries, company sizes, functional specialities, and tenures. McKinsey, *Global Survey on artificial intelligence*, 2020.

[12]See e.g., Thompson (2019).

[13]A general-purpose technology can be defined as a "technology with a range of characteristics which makes it particularly well placed to generate longer-term productivity increases and economic growth across a range of industries". OECD, *The Impacts of Nanotechnology on Companies*. 2010.

[14]The potential economic impact of introducing autonomous vehicles into the economy could be significant due to savings from fewer crashes, less congestion and other benefits. It is estimated that a 10% adoption rate of autonomous vehicles in the United States would save 1 100 lives and save USD 38 billion per year. (Fagnant and Kockelman (2015)).

are also impacted,[15] such as health,[16] finance,[17] agriculture,[18] and justice.[19] As the amount of information generated daily increases, the constitution of large databases and the use of data analytics gets more commoditised and more efficient[20], and the potential impact of AI on people's lives increases.

Concerns about AI. The deployment of AI technologies raises societal, economic and political concerns. According to Acemoglu (2021), if AI "remains unregulated, then it can harm competition, consumer privacy and consumer choice, it may excessively automate work, fuel inequality, inefficiently push down wages, and fail to improve productivity. It may also make political discourse increasingly distorted, cutting one of the lifelines of democracy."

One of main concerns about AI is privacy, as it is used to predict what individuals may want, be influenced by, or do.[21] In 2019, more than 80% of OECD countries considered AI and big data analytics as the primary source of privacy and personal data protection issues.[22] Tucker (2019) argues that privacy is challenging for three reasons: (1) Data Persistence: data may persist longer than the person who generated the data intended, (2) Data Repurposing: data may be repurposed for uses other than initially intended, and (3) Data Spillovers: data created by one individual may contain information about others.[23] Thus, the collection and usage of data to make predictions can harm individuals if they are not fully aware of how their data is collected and used. There may be a trade-off between too little privacy protection, decreasing consumers' confidence and usage, and too much privacy regulation, leading to decreased innovation because firms cannot use data.

Currently, specific characteristics of AI create challenges for ensuring the proper law application and enforcement. In particular, the opacity of AI makes it difficult to identify and prove possible breaches of laws. A public authority (e.g., a regulator) may face two different informational situations when a firm uses AI. First, a firm may have more

[15] See Fagnant and Kockelman (2015) for a review of the impact of AI on these sectors.

[16] In healthcare, AI systems help diagnose and prevent disease and outbreaks early on, discover treatments and drugs, propose tailored interventions and power self-monitoring tools.

[17] Financial services leverage AI to detect fraud, assess creditworthiness, reduce customer service costs, automate trading and support legal compliance.

[18] AI applications in agriculture include crop and soil health monitoring and predicting the impact of environmental factors on crop yield.

[19] In criminal justice, AI is used for predictive policing and assessing reoffending risk.

[20] There are already rapid improvement in areas from image recognition to medical diagnosis. Brynjolfsson et al. (2018) note that error rates in image recognition improved by an order of magnitude between 2010 and 2016.

[21] Acquisti et al. (2016) reviewed the economics literature on privacy.

[22] OECD, *Digital Economy Outlook*, 2020.

[23] See Choi et al. (2019).

information than the regulator over its technology or its behaviour. In this case, the firm voluntarily evades the law by using sophisticated AI. A second case corresponds to a situation in which the AI technology may produce unexpected results, not even expected or understood by the firm. In such a situation, imperfect information about AI outcomes is symmetrical between the regulator and the firm. In this case, the parties face the problem of the lack of explainability of AI, meaning that how the algorithm works and makes decisions is not understandable in human terms without cost.

This raises the question of what regulatory framework should be put in place for the firm to invest in understanding how the machine works and how it makes decisions to limit these unexpected outcomes so that they do not cause social harm.

1.1 Information asymmetry with AI

Using AI technology to enforce existing anticompetitive conducts, such as an explicit coordinated strategy (e.g., algorithmic collusion[24]) or an abuse of dominant position (e.g., search bias to favour one's products) exacerbates the information asymmetry between the regulator and the firm.

Regulators cannot always process and analyse large and complex data sets to cope with the complexity of the technology and the frequency of technological changes. For example, a Wall Street Journal investigation, based on a review of internal Facebook documents, shows that Facebook platforms are "riddled with flaws that cause harm, often in ways only the company fully understands".[25]

Understanding digital technologies often require experimenting with algorithms and specific skills. Several regulators are building teams with such skills, enabling them to deal with the complexity of these technologies (e.g., the Digital Markets Unit in the UK and France).

[24] For example, in the Wall posters case (US DoJ, 2015), the online retailers fixed the prices of posters sold online through the Amazon Marketplace. Assistant Attorney General Bill Baer stated that the Department of Justice's Antitrust Division "will not tolerate anticompetitive conduct, whether it occurs in a smoke-filled room or over the Internet using complex pricing algorithms. American consumers have the right to a free and fair marketplace online, as well as in brick and mortar businesses."

[25] Wall Street Journal investigation, *the Facebook files*, Sept. 14, 2021. In particular, Facebook "found that Instagram is harmful for a sizable percentage of them, most notably teenage girls, more so than other social-media platforms. In public, Facebook has consistently played down the app's negative effects, including in comments to Congress, and hasn't made its research public or available to academics or lawmakers who have asked for it".

1.2 AI explainability

In addition to the asymmetric information problem, the regulator faces a specific enforcement problem with AI technologies. When choosing its AI technology, a firm trades off between technology performance and its ability to explain its decisions and actions in human terms. Often, the best-performing methods (e.g., deep neural networks) are the least explainable, and the most explainable (e.g., simple decision trees) are the least accurate (see Figure 1)

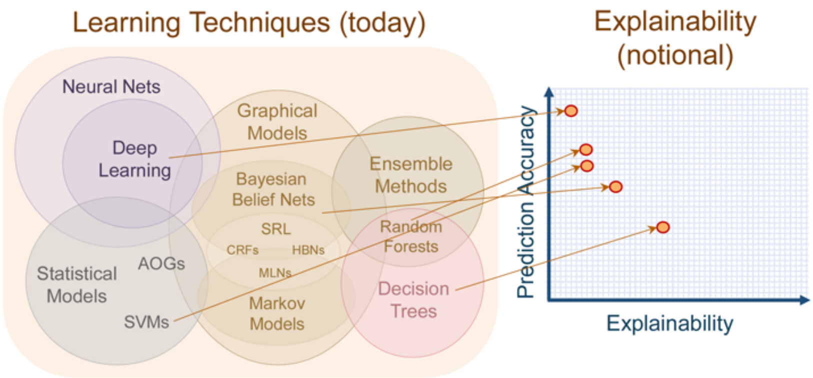

Figure 1: The performance-explainability trade-off of AI (source: DARPA).

The recent success of AI is primarily due to machine-learning techniques and deep neural networks that iterate on the data they are trained on. They find complex, multi-variable probabilistic correlations that become part of the model that they build. However, they do not indicate how data could interrelate (Weinberger (2018)). These can be highly complex and difficult to understand, even for those who program and train them.[26] Moreover, these systems iterate and evolve and may even change their behaviour in unexpected ways. Finally, a specific prediction or decision may not be reproducible, as it only emerges when the machine-learning system is presented with specific conditions and data. Even if there is some research to improve explainability while maintaining a high level of learning performance,[27] currently, in the absence of an appropriate regulatory framework, a firm will often, if not always, choose efficiency over explainability. However, the lack of explainability raises a concern that AI decision-making could lead to unexpected correlations resulting in AI misconduct.

AI technologies misconduct. There is a broad range of potential AI misconduct, from autonomous car accidents (that could be avoided) to biased results that favour men or people from specific socioeconomic backgrounds. Some may result from the

[26] Peña-López et al. (2019).

[27] Deep explanation, interpretable models, and model induction. See, e.g., Gunning and Aha (2019).

use of AI technology by a single firm (e.g., bias or the car accident)[28], others may occur as a result of the use of AI technology by several firms (e.g., AI collusion).[29]

There are two potential sources of misconduct: misspecification of the objective function and biased data training.

First, there are situations in which a human programmer has an objective in mind but the system in which the design is intended to operate produces harmful and unexpected results. It is challenging to design a precise and complete objective function taking into account all bad eventualities that could happen (Hadfield-Menell and Hadfield (2019)). Amodei et al. (2016) provide examples of such situations.

Second, the data used to train the algorithms may be biased, or not accurate enough. These biases may reflect discrimination understood as "unjustified distinction of individuals based on their membership, or perceived membership, in a certain group or category" (Kleinberg et al. (2016)). Cowgill et al. (2020) investigate the formation of biased beliefs in the context of human capital, and show that biased beliefs are caused mostly by biased training data.

Firms' incentives to mitigate AI misconduct. Firms may not have sufficient incentives to mitigate AI misconduct, even if it would be socially beneficial. Some misconduct may serve the firm's interests (e.g., when the damage corresponds to unintentional AI collusion). In other cases, it may be in the firm's interest to reduce AI misbehaviour, but its incentives are too low compared to what would be optimal.[30]

Therefore, regulators need to find mechanisms that encourage companies to invest optimally in precautions to avoid AI mistakes, which are detrimental to society. In particular, firms using AI need to invest in explainability to understand what the technology is doing and thus comply with regulations when the technology misbehaves. Already in 2017, EU Commissioner Vestager emphasised that "companies can't escape responsibility for collusion by hiding behind a computer program".

There are two approaches to AI enforcement: public and private. Private enforce-

[28] See, Fisman and Luca (2016).

[29] Several recent academic studies suggest that relatively basic machine-learning technologies can generate collusion between algorithms - see Calvano et al. (2020), Klein (2019), Abada and Lambin (2020). Calvano et al. (2020) shows that this concern applies to standard reinforcement learning algorithms by demonstrating that they converge on supra-competitive prices. There is still no empirical evidence of the effects of AI on price levels and the intensity of competition in real markets.

[30] As mentioned by Cowgill and Tucker (2019), "economic theory suggests that firms have profit-oriented motives for reducing bias. This is true even without regulatory punishments, fines, lawsuits or bad PR. Firms face normal production and sales reasons to use the most accurate predictions whenever possible. Impediments to adoption may not arise from profit alignment but from other frictions such as awareness, uncertainty about techniques, unavailability of expertise or raw inputs necessary to de-bias algorithms. This does not guarantee firms will give bias reduction their highest priority, but it does suggest that if regulators, vendors and activists can make de-biasing easy, then firms will do it."

ment approaches (e.g., liability) aim to induce the agents generating the damage to internalise the costs of harm that can occur from their activities, by adjusting their incentives to take precautions to prevent this harm through compensation to the injured parties.[31] The public regulatory approach creates incentives through the risk of a potential sanction by a public authority (e.g., a competition authority). There are generally three main reasons to favour public enforcement of law, instead of private tort and contract law.[32] First, information asymmetries may make it difficult for victims to identify the source of the harm. Second, there may be economies of scale and natural monopolies in monitoring and enforcement technologies. Third, positive externalities may arise from harm reduction or negative externalities from private monitoring.

Chapter 1 adopts a public enforcement approach to study the implementation of a (costly and imperfect) audit system by a regulator seeking to limit the risk of damage generated by AI technologies and its regulation cost. Firms invest in explainability to better understand their technologies and, thus, reduce their cost of compliance. When audit efficacy is not affected by explainability, firms invest voluntarily in explainability. Technology-specific regulation induces greater explainability and compliance than technology-neutral regulation. If instead, explainability facilitates the regulator's detection of misconduct, a firm may hide its misconduct behind algorithmic opacity. Regulatory opportunism further deters investment in explainability. To promote explainability and compliance, command-and-control regulation with minimum explainability standards may be needed.

[31] Coase (1960); Calabresi and Bass (1970); Shavell (1980). See also Galasso and Luo (2018) for an overview of the current debates over the application of tort law to AI technologies.

[32] Becker and Stigler (1974), Landes and Posner (1975), and Polinsky and Shavell (2000).

2 The market power of digital platforms

Recent indicators suggest that the competitive intensity may be declining in some digital markets, such as the growth of mark-ups, the decline in the entry of new players and the rise of concentration.[33] Some characteristics of these markets are conductive of concentration. Digital firms, and particularly digital platforms, often benefit from significant returns to scale, network effects or self-reinforcing advantages of data to establish a dominant position. A crucial question is whether digital markets remain contestable for new entrants. In other words, is competition with the big platforms still on the merits? If not, regulatory intervention should be envisaged.

2.1 Digital platforms: the heart of the digital economy

Characteristics of platforms. Platforms are intermediaries that facilitate interactions between individuals or distinct groups of users through a technological interface.[34] They play a crucial role in increasing matching efficiency, reducing transaction costs and improving the quality of service. In the platform model, users interact directly with another type of user. In contrast with traditional firms, users retain control rights over decisions that directly affect the interaction with the other user groups. For example, a business that joins a platform retains control over decisions that affect customer demand (e.g., pricing, advertising, quality service).[35]

Platforms allow interaction between one-sided or multi-sided groups. In a one-sided platforms, users have similar characteristics in terms of interaction objective and no significant distinction can be made between users. For example, users of a communication platform such as WhatsApp want to interact with one another. In multi-sided platforms, the distinction between different groups of users can be made based on the difference of the interaction objective. Some groups want to interact with another specific group. For example, a seller wants to interact with a consumer and not with another seller (e.g., Airbnb connects owners of properties with renters). In this case, besides possible one-sided network effects between users in each group, there are also possible network effects across groups.

[33] OECD Ecoscope Blog, *Competition in the digital age*, May 2019. See also the indicators developed by the EU Observatory on the Online Platform Economy.

[34] For a recent and comprehensive treatment of the economics of platforms, see Belleflamme and Peitz (2021).

[35] For a discussion of what makes a multi-sided platform business model different from traditional alternatives such as vertically integrated firms, resellers or input suppliers, see Hagiu and Wright (2015) and Hagiu and Wright (2019).

Platforms as regulators: competition on the platform. The platform defines its governance rules and technological interface functionalities. Such rule-setting and "market design" determine how competition takes place on the platform (Crémer et al. (2019)).

The main governance rules concern the conditions of access to the platform, the rules governing the relationship between the platform and the users (e.g., the allocation of responsibility), and the rules of interaction between users on the platform (e.g., limits of allowable speech). For example, the platform sets the users' subscription price. When the platform allows different groups of users (i.e. the platform is multi-sided) who generate cross-group network effects, then the prices set for the different groups by the platform do not only reflect the costs of providing the service to them. These prices also reflect the attractiveness of each party to the other through cross-group network effects.[36] Indeed, the platform subsidises the users who generate the most network effects towards the other group. It then captures the value generated by these network effects on the other side. The subsidy can be substantial if network efforts are significant. The subscription price structure for different user groups influences the volume of transactions that occur on the platform.[37]

Platform design choices include, for example, rankings, default options, search filters, feedback and recommendation systems. Such, non-price-based rules generate additional surplus for the platform. The platform also make decisions that can affect the quality of interactions, for example, when introducing reputation systems. Certain features may favour one type of user over another. For example, regulating how sellers present their offers may favour sellers over buyers (e.g., the ability to pay to appear at the top of search results) or vice versa (e.g., minimum requirements). Platforms make governance choices based on the value they can capture, and these choices may not coincide with the social optimum.[38]

Competition among platforms. For platforms, much of the competition revolves around two dimensions: prices and product innovation (Crémer et al. (2019)).[39] Competition in the digital economy is increasingly a competition between ecosystems.[40] In recent years, the most successful digital companies have been building their business

[36] See Rochet and Tirole (2006), Caillaud and Jullien (2003) and Armstrong (2006).

[37] Rochet and Tirole (2006) define "a two-sided market as one in which the volume of transactions between end-users depends on the structure and not only on the overall level of the fees charged by the platform".

[38] See, e.g., Teh (2021).

[39] A recent summary of the relevant literature on the competition with multi-sided platforms is provided in Jullien and Sand-Zantman (2021).

[40] OECD, *Competition Economics of Digital Ecosystems*, 2020.

model around large ecosystems of complementary products and services around their core service, linked through shared functionalities, which benefit the consumers when used together.

2.2 Concentration in platform markets

Three economic mechanisms – scale economies, network effects and the self-reinforcing advantages of data – can increase the concentration of users on a platform and lead to a monopoly outcome. The situation of digital markets in Europe illustrates this dynamic.

Digital markets concentration. Over 10,000 online platforms operate in Europe, most of which are small and medium enterprises.[41] However, a small number of large online platforms capture the most significant share of the overall value generated, with "the 50 top online platforms, representing an average of over 60% of traffic share across the EU Member States, achieved worldwide revenues of almost USD 340 billion (EUR 276 billion) in 2018 [...]."[42] Concentration is particularly prominent in search and display advertising markets, which are dominated by Google and Facebook, respectively.[43] Social media are dominated by Facebook.[44] There is a duopoly between Apple and Google for app stores. Finally, Amazon is the dominant e-commerce marketplace.[45]

Three economic mechanisms generate this concentration around large platforms.

Economies of scale.

Digital products are often produced at a high fixed cost but with low variable costs (Varian et al. (2004)). This generates increasing returns to scale through economies of scale: as sales increase, the average unit cost decreases. Economies of scale favour large firms, making it difficult for new firms to emerge. Potential new entrants face higher costs than incumbents until they can attract a sufficiently high number of users.

[41] EU Observatory on the Online Platform Economy website, September 2021.

[42] Ibid.

[43] Google had a 93.6% share of traffic in December 2020 (EU Platform observatory), while Facebook has over 50% of the display advertising market (The Competition and Markets Authority, *Online platforms and digital advertising market study*, July 2020.).

[44] Facebook is the leader in the social media market in Europe, with a 77.5% share of traffic in December 2020, with some competition from Twitter and Snapchat (EU Platform observatory). Facebook had 2.8 billion monthly active users in December 31, 2020 (FTC Report on Acquisitions by Select Technology Platforms).

[45] Amazon controls about 50% of e-commerce in the US (Tech Crunch, *Amazon's share of the US e-commerce market is now 49%, or 5% of all retail spend*, July 13, 2018).

For example, a search engine requires large technological investments that will cost roughly the same regardless of the number of search requests it will attract.

Network effects.

Network effects arise where a consumer's willingness to pay depends not only on the product's characteristics but also on the number of consumers who use (or are expected to use) the same product or compatible products. As previously mentioned, there are two types of network effects relevant for platforms.

First, there are cross-group network effects. The attractiveness of a platform for the members of one group depends on the participation of users in other groups (e.g., the more people are on Facebook, the more advertisers will be attracted). Second, there may be also within-group network effects. That is, the attractiveness of a platform for users depends on the participation of similar users (from the same group). For instance, sellers' entry into a marketplace decreases the expected profits of other sellers on the platform, which corresponds to a negative within-group network effect.

Network effects represent another source of concentration in digital markets, which can lead to the monopolisation of the market (the "winner-take-all" effect).

Exploitation of data.

Data can also be a source of competitive advantage, increasing market concentration. When data improves products, firms can attract more customers and therefore obtain more data, potentially creating a self-reinforcing cycle that can make it difficult for any new entrant to compete. Hagiu and Wright (2020) show that the ability of a firm to gain market monopolisation dynamics and market power through the exploitation of its users' data varies according to the data and the context. For instance, Deezer's personalised recommendations leverage the user's listening data. It generates switching costs to another music platform for that user but has no effect on other users, and therefore does not lead to market monopolisation. When data instantly improves the firm's product for all users of that product, it results in a significant competitive advantage for the firm and can lead to market monopolisation. In such a situation, users will tend to coordinate on the product for which they anticipate the highest participation. For example, the estimated journey times by Waze (Google's traffic and community application) will be more accurate the more users there are, which will lead to new users adopting the service, which in turn will improve the service, and so on. The mechanism is close to the mechanism at play with network effects. The difference is that the user does not value the presence of other users *per se* but the improvement of the service, made possible by the exploitation of data generated by other users.

2.3 Factors mitigating concentration

Several factors can limit concentration and lead to the co-existence of competing platforms.

Platform differentiation. Different user preferences can lead to a situation in which several platforms coexist despite concentration dynamics. By joining a smaller platform, the user loses the benefits of belonging to a large network but gains the product's intrinsic value. If enough users join the small platform, it can survive even if it attracts fewer consumers. For example, several social media platforms coexist (e.g., Facebook and LinkedIn) because they target different audiences and needs.

Multihoming. If users can use several platforms simultaneously (i.e., multihome), it allows several platforms to co-exist. In particular, a new entrant can convince some users to switch to their platform while still conserving the incumbent platform's benefits to interact with others. If enough users multi-home, several platforms can be sustainable. For example, riders and drivers may have multiple accounts (e.g., on Uber and Lyft). Both can look at both platforms to get the best deal.

Congestion. Concentration may also be limited by congestion. In some instances, additional users can have negative effects on the relative attractiveness of that platform. For example, users will not always join a two-sided platform with a large number of users in the other groups. There is evidence that a user may prefer to avoid a platform that offers too much choice and instead choose a platform that fulfils a curation function, permitting the user to lower its search costs (Tucker (2018)).

Varian (2019) emphasizes that data is a scarce resource that exhibits decreasing returns to scale in a technical sense: prediction accuracy theoretically increases in the square root of the number of observations, suggesting a concave relationship between the amount of data and its value in improving predictions.

Moreover, it may have congestion on the same side of the market when the negative effects from the same side users exceed the positive network effects of interaction with users from the other group. For instance, sellers may face too much competition from other sellers on the platform.[46]

[46] See Karle et al. (2020).

Even with these effects allowing for the co-existence of several platforms, digital markets tend to be concentrated, generating efficiency but also the concern that competition will not discipline enough the dominant platforms.

2.4 Impact of platform concentration

Efficiency versus market power concerns.

Market concentration around large platforms can maximise the overall value generated by scale economies, network effects or data-enabled learning. In other words, it may be more efficient to concentrate production in a small number of firms than to distribute it among many small producers, since this reduces the cost per unit produced (scale economies) or increases value (through network effects and/or data-enabled learning).

Weyl and White (2014) argue that competition may lead to too little concentration in the presence of network externalities. For instance, one platform that contains all users is more valuable than two platforms, each of which contains half of the users. It is because with one platform every user can reach every other user. If platforms were identical, non-interoperable, and users would not multi-home, having several platforms serving the same needs would thus be socially wasteful.

Moreover, concentration does not necessarily imply market power, which is "whether or not the company's scope of action is still sufficiently controlled by competition".[47] Indeed, according to the "contestable market" theory, potential entrants may discipline incumbent firms and mitigate market power. Therefore, incumbent firms have limited possibilities to exploit their market power as they attempt to fend off competitors who try to enter.[48]

However, there are growing concerns that large digital platforms have reached a level of power that threatens the development of the digital economy and the economy as a whole for two reasons. Firstly, the position of some Big-Tech platforms may not be contestable anymore by potential efficient entrants, because of market characteristics (i.e., structural reasons). Secondly, Big-Tech platforms may be able to use their market power to deploy significant barriers to the competitive process and maintain their dominance or extend it into new areas (i.e., behavioural reasons).

[47] German Competition authority, Working Paper, *The Market Power of Platforms and Networks, Executive Summary*, June 2016.

[48] For an introduction to contestable market theory see Baumol (1986) and its early criticisms Schwartz and Reynolds (1983) and Dixit (1982).

Absence of contestability.

In digital markets, incumbent platforms' established dominant positions that may not be contestable by more efficient entrants. This lack of contestability may be due to significant barriers to entry. It may also be due to the difficulty for users to switch to a new firm.

Barriers to entry. Barriers to entry discourage entrants from challenging incumbents, further undermining the competitive process and protecting the dominance of existing firms. The mechanisms discussed above, network effects, economies of scale and data-enabled learning effects, generate significant barriers to entry in digital markets.[49]

In particular, network effects and data-enabled learning effects may cause user coordination problems, making it difficult for an entrant to compete, leading to market failures.[50] To illustrate this point, consider a situation in which consumers' utility for a product has both a standalone component and a network component. Assume further that from a collective standpoint, all consumers would be better off migrating to the entrant in this situation (i.e., the standalone benefit is higher with the entrant).

In this situation, the entrant may fail to conquer the market because of a widespread belief that not enough consumers will migrate. In particular, incumbents generally are focal in the users' choice.[51] That is, everyone believes that all the other consumers believe that no one will migrate. The only way for the entrant to gain market share is to make it a dominant strategy for consumers to migrate. That is, consumers should find it convenient to migrate no matter what other consumers do. Thus, an entrant can only gain market share by offering additional standalone value or charging relatively low (if possible, negative) prices. Entrants will find it profitable to conquer the market only if the quality gap is large enough. This leads to static inefficiency since some higher quality entrants might fail to conquer the market. In addition to this consumer coordination problem, users of the existing platform may face costs in switching to an alternative platform.

Switching costs. Competition may also be dampened because users are discouraged from switching to alternative providers or using multiple firms. This may stem

[49] According to an International Competition Network (ICN) report, most Competition authorities indicated that these factors played an essential role in digital markets' power assessment in the cases they have investigated (77% for network effects, 51% for economies of scale, 49% for data, 44% for consumer bias 41% for switching costs). (ICN, *Report on results of the ICN survey dominance/substantial market power in digital markets*, 2020).

[50] The following discussion is based on Crémer et al. (2019).

[51] An incumbent is "focal" if consumers make their choices conjecturing that all other consumers will not switch. In such a situation, the incumbent conquers the market too often.

from high switching costs. When switching costs are sufficiently high, users may stay with the product of an incumbent firm rather than switch to a product of an entrant they would prefer. Switching costs may appear when users generate content on the platforms (e.g., Youtube, Facebook, Deezer) but are unable to migrate their data to a competing platform. For example, a user uploads various data on Facebook, including photos and personal information, but may not easily download that data and move it to another social media. Instead, the user would have to start from scratch, re-uploading contact details, photos and re-entering personal information to the new platform. As another example, an online seller who has generated hundreds of product reviews and ratings on Amazon may face a similar challenge when considering migrating to a different platform. So, increasing switching costs may be a valuable strategy for the incumbent platform to decrease the contestability of its market position.

Acquisition of potential rivals. Finally, competition may be dampened because users cannot switch to alternative providers. This may arise from the acquisition by incumbent platforms of entrants that compete with them. Many acquisitions have taken place before any real competition can develop, such as Facebook's acquisition of WhatsApp and Instagram. Overall, since 2000, the GAFAM[52] tech giants have acquired about 1,000 firms.[53] In some instances, these acquisitions enabled the dominant firm to neutralise a competitive threat. In other cases, the dominant firm shut down or discontinued the underlying product entirely–transactions aptly described as "killer acquisitions".[54]

Factors mitigating the lack of contestability. Several factors may limit the extent to which the position of established platforms is not contestable.

First, barriers to entry to a market are generally not widespread across the digital space. For example, network effects tend to be relatively localised. Indeed, the more a network is fragmented into local clusters, and the more isolated those clusters are from one another, the more vulnerable a business is to challenge (Zhu et al. (2021)).

Zhu et al. (2021) compare Uber's market with Airbnb's. Uber drivers in Paris care primarily about the number of riders in Paris, and riders in Paris care mostly about drivers in Paris. This makes it easy for another ride-sharing service to reach the critical mass in a local market thanks to a differentiated offer (e.g., a lower price). Thus, in addition to its rivals at the national level, Uber confronts many local threats. By

[52] Google, Apple, Facebook, Amazon and Microsoft.

[53] FTC Study, *Non-HSR Reported Acquisitions by Select Technology Platforms*, 2021. See also, e.g., Cabral (2021) and Cabral et al. (2021).

[54] See also Pike (2020), Federico et al. (2020) and Letina et al. (2020).

contrast, travellers do not consider Airbnb hosts in their home cities. Instead, they care about hosts in the cities they plan to visit. Any challenger to Airbnb would have to enter the global market-building brand awareness worldwide to attract critical masses of travellers and hosts. So, breaking into Airbnb's market is much more costly.

Second, barriers to entry may be challenged through radical innovation. A technological breakthrough or the emergence of a more innovative competitor has already destroyed the position of a once-dominant firm several times in the digital economy. For example, the web browser market has been dominated successively by Netscape, Internet Explorer, and Google Chrome.

Implications The lack of contestability generates significant market power with the ability to impose high prices or degrade quality for captive consumers. This may require regulatory intervention.

Excessive prices or rents. Market power allows large platforms to increase their prices, leading to economic inefficiency. For example, Google's advertising prices are 30-40% higher on desktop and mobile when comparing similar search terms to Bing.[55] Facebook's average revenue per user in the UK in 2019 was significantly higher than its competitors.[56] As mentioned by the CMA report, "weak competition in digital advertising increases the prices of goods and services across the economy and undermines the ability of newspapers and others to produce valuable content, to the detriment of broader society." Similarly, the fees paid by the merchants, so that their goods and services are listed and recommended by the platforms, increase consumer prices.

Excessive prices are not the only problem with monopolies. As John Hicks pointed out in 1935: "The best of all monopoly profits is a quiet life." In other words, the monopoly tends not to control its costs. It may then have the opportunity to pass on its costs to consumers; it has no incentive to reduce them. Moreover, the dominant firm has little incentive to pass on its productivity gains to consumers.

According to the Digital regulation project[57], rents from digital technology are unfairly distributed to a handful of large platforms instead of being more fairly distributed according to each party's contribution to the surplus. All users as a group contribute very substantially to the total surplus, as most of the surplus is likely to arise from their ability to interact with each other on the platform rather than from the specific characteristics of a particular dominant platform. However, a complementary individual user

[55] The Competition and Markets Authority (CMA), *Online platforms and digital advertising market study*, July 2020 (the "CMA Report").

[56] Ibid.

[57] Digital regulation project, *Fairness and Contestability in the Digital Markets Act*, July 2021.

makes a tiny marginal contribution to surplus creation. Thus, when an individual user trades a share of the surplus, his leverage is low.

This low bargaining power of users also translates into the existence of potentially "unfair" trading practices imposed by platforms, such as imposing unfair terms and conditions.

Degraded quality. Platforms can engage in non-price practices that are favourable for them while degrading the product quality for their consumers. Platforms may collect an excessive amount of data from their users, undermining their privacy. This includes creating incentives for users to spend more time on a platform. In particular, this might be the product of emotional manipulation.[58]

Another example can be Google's search results. When comparing today's search results with those of ten years ago, user experience is degraded due to the predominance of paid content for specific searches.[59]

These practices are related to the economic dependence and imbalanced bargaining power between the platform and its users. The main quality issues of the platforms' provision identified by business users are sudden unilateral changed in the access terms and conditions, delisting and suspension of accounts, favouring own services, and so on.[60] For instance, Facebook cut off Vine's access to its "Find Contacts" feature once it was acquired by competing social media platform Twitter in 2013.[61]

Reduced incentives for innovation. Finally, the absence of competition may reduce the incumbent's incentives to innovate. Indeed, since innovation is a means of improving a firm's market position over its competitors, if the likelihood of entry by competitors is reduced, then innovation is less necessary to protect a market position.[62]

[58] Stigler Center report, *Digital Platforms Market Structure and Antitrust Subcommittee Report*, September 2019. ("Stigler report"). See also Wall Street Journal investigation, *the Facebook files*, Sept. 14, 2021.

[59] Digital regulation project, *More Competitive Search Through Regulation*, Appendix 3, May 2021.

[60] European Commission report, *Business-to-Business relations in the online platform environment*, 2017.

[61] The CMA report, para. 3.231.

[62] However, there is no consensus on whether market power reinforces or discourages innovation. Firms have incentives to innovate to escape from competition (Aghion et al. (2005)). Firms with monopoly rents have a greater incentive to innovate to protect their position. Most of the theoretical contributions have focused on the interaction between these two opposing forces for different market structures and innovation characteristics.

Abuses of dominant position

Big Tech platforms may also use their market power to engage in anticompetitive practices to artificially raise barriers to entry or to conquer additional rents by distorting competition. We will briefly review the main theories of harm of anticompetitive behaviour associated with digital platforms.[63]

Exclusion of nascent threats or increasing barriers to entry

Predatory pricing. Predatory pricing refers to a dominant firm's foreclosure strategy that prices below cost in the short term to drive its competitors out of the market. It then seeks to recoup its losses with higher prices. Determining whether low pricing in a digital market can qualify as an predatory practice is challenging. There are several offsetting efficiency justifications for providing digital products for free. First, it may reflect a freemium strategy: a firm offers both a zero price version of a product and a paid premium version.

Second, the price may take the form of data provided by the users of the product (i.e., free data for free services). In particular, in multi-sided markets users pay with their data and attention, which can be monetised with an other side of the platform (e.g., advertisers' side). Moreover, as described above, multi-sided digital platforms often involve cross-subsidisation between different market sides. So, low prices on one side of a platform can also be a strategy for maximising network effects, such as attracting a user base to increase the platforms' value to consumers on another side of the market (where the losses could be recouped).

Several firms in digital markets have also acquired large market shares without being profitable for extended periods (e.g., Amazon or Uber).

Tying, bundling and other related practices. Tying, bundling and other related practices (e.g., pre-installed apps) may be used as a means to foreclose competition.[64] By requiring users of one of its products to buy another product, a monopoly firm can deny market access to new entrants. This is particularly detrimental to new entrants, as they often start with a niche product and then expand to a wider range of products (e.g. books for Amazon, the search engine for Google).

[63] See OECD, *Abuse of dominance in digital markets*, 2020 for a more comprehensive view on the subject.

[64] A survey of the literature on the potential anticompetitive consequences of these practices is provided in Rey and Tirole (2007). Several recent papers examine how the theory should be modified to consider the specific features of digital markets, see Choi and Jeon (2021).

Extension of market power into adjacent markets

Self-preferencing. Big Tech platforms often operate as both a marketplace for third-party products and a seller of their own products on that same marketplace. This “hybrid” model can give rise to conflicts of interest. This practice has raised regulatory concerns over the lack of a level playing field.

Platforms may bias the matching in a direction favourable to them while being unfavourable to users[65] – for example, Booking favours affiliated hotels that do not offer lower prices on their websites (Hunold et al. (2018)).[66]

On 30 April 2021, the European Commission reached the preliminary conclusion that Apple distorted competition in the music streaming market as it abused its dominant position for the distribution of music streaming apps through its App Store. It required its rivals to use Apple’s in-app purchase system to sell subscriptions via their apps and pay a 30% commission. Its contracts also included ”anti-steering” clauses, which prohibited these services from telling their users that they could get a better deal by subscribing directly on the website.[67]

There are several cases where platforms seem to have misused the unique access to data in their position as both player and referee. For example, every business that sells on the Amazon marketplace generates data about what people buy, which helps them set prices and choose products to sell. However, these businesses only know about their customers. Amazon has data about the entire marketplace: for each seller, it knows how much they sold of each product, how much revenue they made, which offers were most interesting to customers, etc. On November 2020, the European commission reached the preliminary conclusion that Amazon misused that data to compete against those sellers when Amazon itself sold products on its marketplace.

On June 2021, the European Commission opened an investigation into the possible anticompetitive conduct of Facebook, consisting of using advertising data collected from advertisers to compete in markets where Facebook is active, such as classified ads.

Tying, bundling and other related practices. Tying, bundling and other related practices may be used as a means to leverage market power from one market to

[65] See Hagiu et al. (2020) for a theoretical approach of this issue.

[66] See the US House of Representatives report on competition in digital markets provides several examples of alleged self-preferencing by Amazon. US House of Representatives Sub-Committee on Antitrust, *Investigation of Competition in Digital Markets*, Washington, 2020.

[67] European Commission press release, *Antitrust: Commission sends Statement of Objections to Apple on App Store rules for music streaming providers*, 30 April 2021.

another market using such a strategy (see, e.g., Windows Media Player (2004) and Google Android (2018)[68]).

[68]Google made access to its app store conditional on the pre-installation of its search app and browser on Android devices. The apps pre-installation reduced the incentive for manufacturers and users to use competing apps, harming competition. (European Commission Press Release, *Commission fines Google €4.34 billion for illegal practices regarding Android mobile devices to strengthen dominance of Google's search engine*, 18 July 2018.

2.5 Regulating the market power of digital platforms

The lack of contestability and the identification of market behaviours of Big Tech platforms that threaten competition should lead to a public intervention to restore an economic system based on the merits. Intense policy discussions on how to design and implement platform regulation are currently ongoing.[69]

Ex-ante regulation. Many possible measures have been considered to limit the market power of large digital platforms and restore contestable digital markets.[70] The first idea would be to apply a similar treatment to what prevailed in network industries (e.g., telecoms, electricity).

Applying utility regulation (i.e., cost-of-service and incentive regulation) to digital markets is challenging for two reasons. Firstly, the regulator should monitor the platform throughout its life cycle to measure its investment cost and estimate its (unobserved) probability of success to give it a reasonable rate of return. Second, unlike traditional network industries, technology giants are global companies, operating with inputs shared across multiple countries (intellectual property, data, servers, supply chain, logistics, sales). In this context, a supranational regulator is needed to determine the appropriate rate of return and the distribution of contributions across territories and activities.

An alternative approach to regulating the entire activity of a big platform is to isolate an "essential facility" segment.[71] This segment remains regulated and is constrained to provide a fair and non-discriminatory access to competitors in segments that do not exhibit natural-monopoly characteristics and therefore can sustain competition. This was the rationale for the American Telephone & Telegraph (AT&T) divestiture in 1984. Local operations were split into seven independent regional firms (the Baby Bells) that remained in charge of the local loop, which was perceived as hard to duplicate, while competition enabled long-distance and international calls.

Such a solution is complex to apply in digital markets. First, it requires identifying a stable essential facility. It must be stable because divestiture takes a while to be performed, and implementing access to the essential facility would not be worthwhile if it keeps changing. This condition may not be met. While the technology of elec-

[69] There have been several reports on the evolution of regulation of the digital economy, in particular Crémer et al. (2019), the Furman report, and the CMA report, and the Stigler report. These reports, despite some differences, exhibit a fair amount of convergence. See Combes et al (2019) for French language readers.

[70] See Tirole (2020).

[71] An essential facility is an input whose access is strictly necessary (or indispensable) to exercise an economic activity.

tricity, railroads and telecommunications have not changed much since the early 20th century, digital technologies are moving fast. The regulator's task to identify, collect data and regulate essential facilities is made particularly difficult when technologies are constantly changing. Second, the gains of breaking up the incumbent are uncertain. In particular, the expected competitive gain must be weighed against the loss of efficiency of the natural monopoly, such as economies of scale. For example, breaking a social network into two social networks might not raise consumer welfare. Either consumers will be split into separate communities, preventing them from reaping the benefits of network effects. Alternatively, separated from their friends, they will re-join one of broken-up site, creating the monopoly again. Finally, dominant firms may strategically increase the difficulty to break them by intertwining different services.

Competition policy. Competition law gives some tools to restore competition and to keep markets open. As seen above in Section 2.4, the European Commission has pursued several practices with competition law tools. Some remedies seem to be working, in particular when there are adaptable with a continuous improvement process. For example, following the European Commission's Android decision to restore competition for browsers and search apps on Android tablets and phones,[72] Google introduced in 2019 a "choice screen" that allows Android users to pick the browser and the search app they want as default. Since then, the Commission has been working with Google to make sure the choice screen does give its rivals a chance to compete.

However, competition law procedures can be slow compared to the pace of change in the digital economy. Remedies may be insufficient and outdated to restore competition once the harm has been done. The Google Shopping investigation took seven years, and it remains unclear whether the remedies solved the identified problem.[73] Moreover, competition policy exposes incumbents to legal uncertainty. Indeed, with new issues and an emerging doctrine, dominant firms may not be able to avail themselves of clear guidelines on what they can and cannot do. While competition policy will always embody a retrospective component, this raises the question of a more prospective approach based on a code of competitive conduct, indeed one that is adapted to the speed of digital markets.

Combining competition policy and regulation. One possibility for the regulation of digital platforms would be a combination of the traditional regulation of natural monopolies, with the establishment of certain ex-ante obligations and competition law.

[72] European Commission, decision 40099, *Google Android*, 18 July 2018.

[73] Between 2010 and 2017. European Commission, decision 39740, *Google Shooping*, 18 December 2017.

This new regulatory framework converges to impose special conditions on platforms having "significant and durable market power"(US House of Representatives Majority Staff report[74]), "substantial market power" (ACCC report[75]), "strategic market status" (Furman report[76]) or "bottleneck power" (Stigler report[77]

This identification of the key players helps to limit the information requirements of competition law. This is reflected in the Digital Markets Act (DMA) policy proposal[78] that replaces the traditional three-step competition procedure in the EU (i.e. market definition, identification of dominance) with a single step, namely, identifying gatekeepers and their core services on platforms. It is no longer necessary to (i) study substitution models to delineate markets, (ii) analyse the effects of a particular firm's behaviour and (iii) design and test appropriate remedies - tasks that are also slowing down traditional competition cases. Once a platform has been designated as a gatekeeper, several obligations or conduct principles may be imposed. The obligation of these structuring platforms could be, for example, the pre-notification of their acquisitions, the prohibition of self-referencing and the preferential display of their services. Implementation, as several reports have suggested, could be done by a specialised regulatory agency. Like a regulator, it would collect data about dominant firms and build industry-specific knowledge on how the sector works. It accordingly would have a more forward-looking approach than current competition authorities, with the definition of codes of conduct. Like traditional antitrust, this regulator would avoid setting a price level and determining a rate of return.

Nevertheless, a regulatory intervention that targets a platform's market power should not decrease value creation from the operation of the platforms. In particular, interventions should not reduce structural platforms' efficiency while also encouraging entry and innovation. One way would be to share the sources that generate the dynamics of market monopolisation, for example, allowing or imposing different companies to share network effects of the market to provide their services. One approach to increase the contestability of a structural platform is to allow smaller firms to share and commonly improve the management of their network effects. Another would be a direct sharing of the network effects between the structural platforms and an entrant. This could be achieved by the imposition of interoperability.

[74] US House of Representatives Majority Staff Report, Investigation of Competition in Digital Markets, October 2020.

[75] ACCC report, Digital Platforms Inquiry, Final Report, June 2019.

[76] Furman report, *Unlocking digital competition*, March 2019.

[77] Stigler Center report, *Digital Platforms Market Structure and Antitrust Subcommittee Report*, September 2019. ("Stigler report")).

[78] European Commission, *Proposal for a regulation of the European parliament and of the Council on contestable and fair markets in the digital sector (Digital Markets Act)*.

Platform coopetition. Cooperation may improve contestability by allowing small players to share network effects with incumbents. Cooperation between competitors may be beneficial for the social surplus. Indeed, firms cooperating may increase then effort to decrease their production costs or increase their production value. For example, firms can achieve better production efficiency by pooling risk, inputs and buyer power or exploiting scale economies or network effects. Each firm part of the cooperation brings some complementarity to the other firms to increase overall profitability. This type of cooperation is valuable from a social point of view.

To achieve the benefits from cooperation and, at the same time, safeguard a competitive environment, platforms should generally continue to compete on some other strategic variables. This situation is called coopetition, i.e., competitors are induced to cooperate on some variables while competing on other variables. However, cooperation between competitors may also be problematic from an efficiency perspective. It may be used to gain market power in order to increase profit by reducing competition. This generally decreases total welfare and is prohibited by competition law.[79] Such practice is referred to as "collusion". There is thus a complicated exercise to assess whether a cooperative agreement is a collusion practice (i.e., likely to reduce competition and raise the price) or a coopetition practice (i.e., likely to generate additional total surplus).

Allowing smaller firms to share and improve the management of their network effects may translate into letting them coordinate on an instrument that affects the multihoming of users while ensuring a fair distribution of the value created to users through competition. Indeed, because multihoming benefits are allocated through different intermediaries, each platform may not fully internalise the surplus generated by such practices.

Chapter 2 studies the effect of price coopetition between two platforms in a growing market (i.e., in which new users can join the platform) and in a mature market.

[79] Starting with the Sherman Act Section 1 prohibition of any contract, combination in the form of trust or otherwise, or conspiracy, in restraint of trade or commerce (1890), the prevention of lessening of competition through agreements among potential competitors has been one of the two cornerstones of competition policy. Article 101 of the European Treaty provides a similar prohibition in the EU. The other cornerstone is monitoring abuses of dominant positions (Section 2 of the Sherman Act, Article 102 of the European Treaty).

Platform interoperability. Interoperability refers to "the ability of two or more systems or components to exchange information and to use the information that has been exchanged".[80] Interoperability between two platforms is the ability of a user on one platform to send information to users on another platform. This allows network effects to be shared between different platforms, thereby reducing the importance of network effects in users' choice of subscription to a platform.

Many services are already interoperable on the Internet (e.g., email) or become interoperable. Part of this interoperability stems from a strategy to make all of its platform products interoperable to favour them and thus be protected from competition. This "annexation" strategy[81] can be illustrated by Facebook's announcement of its intention to make Facebook Messenger, WhatsApp and Instagram interoperable so that users of one application can send messages to users of other applications using the service they prefer.[82]

Mandatory interoperability between an incumbent and a new entrant can be a powerful regulatory tool. Indeed, the implementation of platform interoperability would remove the advantage of a dominant platform as its installed base of users would be accessible directly from another competing platform.

Currently, if the platforms present in the market are differentiated, the only way for the consumer to access users not present on his preferred platform is to multi-home, i.e., frequent another platform in addition to his preferred platform.

So, interoperability is often cited as a possible regulatory tool to stimulate entry and enhance contestability in digital markets.[83] The implementation of this regulatory tool may seem particularly cumbersome, but Chinese digital players Tencent and Alibaba already appear to be starting to implement interoperability only months after the Ministry of Industry and Information Technology decided to mandate interoperability.[84] Moreover, interoperability measures are not new as regulatory tools. Interoperability between the networks of different telecoms operators has eliminated many network effects, so that the trend towards concentration is linked to the nature of costs. A telecom user can make phone calls to people in other networks than its telecom operator. We study this regulatory solution for digital markets in Chapter 3.

[80] IEEE Standard Computing Dictionary (IEEE, 1990).

[81] Scott Morton (2021) collects examples and explains this type of strategy.

[82] Mark Zuckerberg, *A Privacy-Focused Vision for Social Networking*, 6 March 2019.

[83] OECD Competition Committee, Working Paper, *Data Portability, Interoperability and Competition of Digital Platforms*, June 2021.

[84] Finacial Times, *Tencent and Alibaba pledge to open up apps to competitors*, 13 September 2021.

3 Thesis contributions and outline

We have seen in this introduction that digital markets can lead to several market failures that come from structural barriers to entry and facilitates the creation of artificial ones. There has been much discussion about what would be the most appropriate way to address them. This thesis aims to contribute to this debate and to the development of an appropriate regulatory framework for the digital economy. In particular, this thesis contributes to the theoretical economic literature on digital markets in three ways.

In Chapter 1, I study the regulation of the use of artificial intelligence. With Xavier Lambin, we formalise the trade-off of firms in their choice of artificial intelligence technology between performance and the technology's ability to be understood by humans. In the absence of a regulatory framework, companies generally choose performance over the explainability of their technology. The introduction of a regulatory framework is therefore desirable when there is a risk that the use of the technology will cause harm. In our model, the costly investment for the company allows it to reduce its compliance costs.

We show that the regulatory framework must be chosen carefully. On the one hand, firms may strategically decrease explainability when regulatory audits are imperfect to escape regulatory oversight and sanctions. On the other hand, limiting regulatory costs may lead the regulator to choose to control firms that have invested in explainability because the damage is easiest to detect. Thus, we find that technology-specific regulation should be preferred to technology-neutral regulation when explainability does not strongly affect the effectiveness of detection by the regulator. Conversely, when explainability strongly affects the regulator's detection efficiency but does not strongly affect firms' compliance costs, technology-neutral regulation should be preferred to avoid excessive regulatory opportunism.

In Chapter 2, I explore cooperation between competing platforms. In the digital economy, it is not always straightforward to determine whether companies are competitors or not, as their respective products may have characteristics of substitutability or complementarity depending on each situation. I study an extreme case in which two two-sided platforms cooperate on the price to be set on one side of the market but still compete on the other side of the market.

I show that platforms internalise the fact that reducing their price on the side where they cooperate will harm the rival platform by making it less attractive to users on that side of the market (e.g., sellers) and, through indirect network effects, to users on the second side as well (e.g., buyers). Consequently, this cooperation leads platforms to increase their subscription price on the side where they cooperate compared to the arm's length case. However, as sellers become more valuable (i.e., by paying more for their subscription price), the platforms' competition to attract buyers intensifies to exert a pull effect on sellers to join their platform. This leads to a lower price for buyers. I show that this coopetition situation can only increase the total surplus relative to total competition if price competition increases the number of buyers in the market.

In Chapter 3, I contribute to the debate on the appropriate tools to limit the absence of contestability of specific Big Tech platforms and facilitate entry. With Guillaume Thébaudin, I study the effects of interoperability between two platforms with different user bases. The large platform (e.g., incumbent) has captive users, acquired through a past presence on the market, and the small platform (e.g., entrant) does not. The introduction of interoperability allows users to interact directly with users on the other side present on the other platform. The question under consideration is what is the right level of interoperability. Different levels of interoperability can be interpreted as different levels of interconnection quality or the possibility to use all interconnection functionalities (e.g., image or video transfer). Users can multihome on both sides of each platform. Two users can therefore meet on both platforms. We assume that they do not get any additional value by interacting a second time.

We show that the optimal level of interoperability to be set by a market regulator depends on its objective. If he wants to maximise user surplus, then it is optimal to implement full interoperability, as users benefit from interacting with all other users in the market by staying on their preferred platform. In a context where the small platform has not yet entered the market, and the regulator wishes to maximise the probability of entry if it requires fixed costs, then setting an intermediate level of interoperability – that maximises the entering platform's profit – would be optimal. Finally, the level of interoperability that maximises total welfare is either full interoperability or zero interoperability, depending on the parameter values.

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Chapter 1

Algorithmic explainability and self-regulation under regulatory audits

"Algorithms must not be a black box and there must be clear rules if something goes wrong" Ursula von der Leyen, State of the Union, September 2020.

1 Introduction

An increasing number of important decisions involving important business activities such as price-setting, advertising, and arriving at loan agreements, are delegated to artificial intelligence algorithms.[1] Over the past decade, these technologies have made staggering progress that may bring sizeable benefits to firms, consumers, and society as a whole. There is, however, mounting concern that these algorithms may take undesirable or even illegal decisions on behalf of their makers–sometimes without their knowing. To illustrate this point, the complaint filed against the AI-hiring firm HireVue in 2019 voiced concerns that unproven artificial intelligence systems that scan people's faces and voices may pave the way for wide-scale threats to workers, including discrimination and other forms of bias. Following an internal audit in 2021 the controversial feature was discontinued. With suspicion regarding the secrecy and lack of explainability of advanced machine-learning tools rising, vendors like HireVue have come under increased scrutiny, and many institutions (e.g., the EU Commission,[2] the State of California, the City of New York, the US[3]) are laying the foundations for algorithmic regulation and auditing.

Explainability is generally defined as the extent to which an algorithm can be ex-

This chapter is co-authored with Xavier Lambin.

[1] A possible definition of artificial intelligence may be found in Acemoglu and Restrepo (2020): "[Artificial Intelligence] refers to the study and development of 'intelligent (machine) agents', which are machines, software, or algorithms that act intelligently by recognising and responding to their environment."

[2] See, e.g., the EU Commission's proposal on AI, published in April 2021

[3] See, e.g., the draft Guidance for Regulation of Artificial Intelligence Applications of the White House's Office of Science and Technology Policy published on January 7, 2019.

plained in human terms.[4] The concept is closely related to the concepts of interpretability and transparency.[5] In the present paper, we use a very narrow definition of explainability: it is the extent to which the potential for misconduct facilitated by an algorithm can be identified by humans (the manager of the firm that operates the algorithm, or a regulator).

When choosing their technology, firms face a trade-off between performance and explainability; often, the best-performing methods (e.g., deep neural networks) are the least explainable, while the most explainable (e.g., basic regressions or simple decision trees) are the least accurate.[6] In the absence of an appropriate regulatory framework (or effective consumer reactions[7]), the firm will often if not always favor the efficiency of a technology over its explainability. While 39% of companies recognise the risk associated with "explainability", only 21% say they are actively addressing this risk.[8] Amodei et al. (2016) collect situations involving such risks in which a human designer has an objective in mind but the system in which the design is intended to operate produces "harmful and unexpected results".[9] Sometimes, such "misconduct" may serve the firm's interest (e.g., when the damage corresponds to unintentional AI collusion).[10]

[4]Lu et al. (2019) propose a framework grounded in philosophy, psychology, and interpretable machine learning to investigate and define the characteristics of a good explanation and conduct a large-scale lab experiment to measure the impact of various factors on perceptions of understanding, fairness, and trust within a loan-application context.

[5]Transparency sometimes involves asymmetric information between a regulator and a firm. In contrast, with explainability, information is usually symmetric but possibly imperfect.

[6]While recent research has made advances in developing interpretable machine-learning models, Barredo Arrieta et al. (2020) and Bertsimas et al. (2019) note that algorithmic interpretability comes at the cost of accuracy.

[7]Our paper takes a public enforcement approach rather than a private enforcement approach (e.g., liability). See Galasso and Luo (2018) for current debates over the application of tort law to AI technologies. We might favor public over private enforcement because the complexity of the technology may make it difficult for victims to identify the source of the harm.

[8]McKinsey & Company survey of 2,360 company respondents, each answering questions about their organisations. "Explainability" is defined in the survey as the ability to explain how AI models come to their decisions. The full results of this survey are available at https://www.mckinsey.com/featured-insights/artificial-intelligence/global-ai-survey-ai-proves-its-worth-but-few-scale-impact.

[9]See also Hadfield-Menell and Hadfield (2019), who bridge issues with the use of algorithms to issues with incomplete contracts. Their main claim is that aligning robots with humans will inevitably require importing into their assessment of rewards the costs associated with taking actions tagged as wrongful by human communities.

[10]Several recent academic studies suggest that relatively basic machine-learning technologies can generate collusion between algorithms - see Calvano et al. (2020), Klein (2019), Abada and Lambin (2020). Calvano et al. (2020) show that this concern applies to standard reinforcement learning algorithms by demonstrating that they converge on supra-competitive prices. There is still no empirical evidence of the effects of AI on price levels and the intensity of competition in real markets. In other situations, a firm has insufficient incentive to resolve AI misconduct even if it is socially beneficial (e.g., when the damage corresponds to algorithmic bias. As mentioned by Cowgill and Tucker (2019), *"economic theory suggests that firms have profit-driven motives to reduce bias. This is true even in the absence of regulatory sanctions, fines, lawsuits, or bad public relations. Firms face normal production and sales*

When the lack of explainability is detrimental to social welfare, regulatory intervention may be warranted.

Two broad approaches are typically considered by actors seeking to avoid and correct damage generated by AI technologies.[11] First, command-and-control (or input) regulation requires firms to adopt specific technologies or to remove sensitive variables from algorithms. Second, outcome regulation allows firms to decide how they will comply with output requirements most efficiently given their circumstances. This creates incentives for firms to invest in technology to meet and possibly go beyond the regulatory standards. Under command-and-control regulation, there are no incentives for an individual firm ever to go beyond what the government has asked. Milli et al. (2019) formalises output regulation and traces how the incentives created by such regulatory schemes affect the downstream choices of machine-learning engineers. To detect and deter misconduct, a regulator adopting an output regulation would traditionally audit a firm with some probability and impose a penalty when misconduct is identified. This solution requires time and financial resources. This is particularly the case when auditing algorithms where adequate expertise remains rare and costly. To limit regulatory costs, a regulator may want to promote self-policing by a firm, which makes the need for an audit less urgent. Indeed, the threat of punishment may be sufficient to induce the firm to seek to identify misconduct prior to taking the algorithm to market – and prior to exposing the firm to a regulatory intervention.[12]

In this paper, we consider a firm that operates a technology that may engage in "misconduct" (i.e., harm social welfare). The regulatory environment penalises misconduct, inducing the firm to intensify its compliance efforts (e.g., by implementing self-audit procedures). In case misconduct is identified by the firm, the issue is remedied prior to rolling out the technology and there is no fine. Explainability, which comes at the firm's cost, helps the firm understand the behavior of its own technology. More specifically, in our model, explainability lowers the marginal cost of compliance. In contrast with compliance, explainability is observed publicly: we will note that it acts as a signalling

reasons to use the most accurate predictions whenever possible. However, the alignment that the bias reduction motives of profit-oriented companies "does not guarantee that companies will give the highest priority to bias reduction.").

[11] See Cowgill and Tucker (2019) for a survey.

[12] Examples of technology companies that operate "responsible artificial intelligence" divisions include Facebook and Google. This was the privileged solution in responses to public consultation on the European Commission's draft regulation: "more than 50% of respondents [...] favoured the [enforcement] model combining ex-ante risk self-assessment and ex-post enforcement for high risk AI systems" (Proposal for a regulation of the European parliament and of the Council laying down harmonised rules on artificial intelligence). This is also in line with what the firms currently "reportedly do to mitigate AI risks [as] the most frequently reported tactic is conducting internal reviews of AI models", as the McKinsey survey reports. Prior EU regulations, including the European Union General Data Protection Regulation (GDPR), have already impose a "right to explanation" when influenced by algorithmic decision-making.

and commitment device of strong compliance.

We compare a firm's equilibrium explainability in two distinct regulatory regimes: technology-neutral and technology-specific regulation. Technology-neutral regulation arises naturally when the explainability level is firm's private information. In that case, the regulator maintains the same audit frequency for all technologies, irrespective of the observed level of explainability. When the explainability level is public information, technology-specific regulation is possible. In that case, the regulator observes the explainability level before auditing begins and may adjust the audit frequency accordingly.

To the best of our knowledge, the present paper is the first to model technology explainability as a firm's strategic choice. Also novel is the explicit acknowledgement that explainability affects the firm's ability to comply with regulation as well as the efficacy of regulatory interventions.

Our results may be summarised as follows. When efficacy is not affected by explainability, firms voluntarily invest in it. Explainability may also, however, render regulatory audits more efficacious, which would deter investment in explainability. When explainability strongly affects audit efficacy, there may be no investment in explainability at all and firms may even actively obfuscate their algorithms so as to hide behind less transparent processes. Under technology-specific regulation, the regulator rationally anticipates that a firm which invests robustly in explainability is more likely to be compliant. As a consequence, the regulator rationally lowers the frequency of auditing it applies to explainable technologies. This mechanism strengthens the firm's incentives to invest in explainability. A regulator may also, however, take advantage of the latter effect strategically by increasing the audit frequency with which it audits explainable technologies where the audit is more likely to be successful. This behavior, which we call "regulatory opportunism", weakens firms' incentives to invest in explainability. When this effect is too strong, technology-neutral regulation should be preferred.

Our analysis has important policy implications for the regulation of algorithms. First, we observe that firms may reduce explainability strategically when regulatory audits are imperfect, as doing so enables them to evade regulatory monitoring and punishment. Second, we show that, when explainability does not strongly affect regulatory efficacy, technology-specific regulation should be preferred over technology-neutral regulation. Conversely, when explainability strongly affects regulatory efficacy but does not strongly affect the cost firms bear for compliance, technology-neutral regulation should be preferred, so as to avoid excessive regulatory opportunism.

The remainder of the paper is organised as follows. In Section 2, we review the literature. In Section 3, we describe the base model. In Section 4, we analyse the benchmark case of technology-neutral regulation, and in Section 5, the case of technology-specific regulation. We conclude in Section 6.

2 Literature review

This paper relates to three streams of literature.
The first stream concerns the analysis of the use of algorithms in decision-making. Athey et al. (2020) study decisions to delegate decision-making to either a human agent or an algorithm. Similarly, Dogan et al. (2018) studies adoption and utilisation of automation in firms with varying organisational structures by developing a theoretical model of organisational design with embedded cheap-talk. In our model, the firm has already decided to use an algorithmic solution but must calibrate the explainability of its AI technology.

Second, our paper relates to the economics literature on optimal law enforcement. How a firm responds to changes in enforcement policies has been discussed extensively in the literature for many years. Becker (1968) was the first to formalize the inclusion of economic considerations in studies of law enforcement (see, e.g., Polinsky and Shavell (2000) and Shavell (2009) for a survey). The literature has emphasised the several issues related to public enforcement. In particular, firms may respond by undertaking avoidance activities that make detection more difficult. Malik (1990) models the implications of attempts by agents trying to reduce the probability that they will be sanctioned by engaging in evasion, lobbying, or concealment efforts. He shows that larger penalties increase incentives to engage in avoidance activities, so an optimising enforcement agency may not choose the stiffest possible sanction. We obtain a similar result with our model, where the firm would choose to obfuscate its technology when the regulatory regime is too stringent.

Heyes (1994) expands these ideas to include a case where a regulator trades off the frequency of inspections against their thoroughness. More frequent inspections encourage concealment, while more thorough inspections encourage transparency. In addition, regulators have developed valuable tools, such as leniency and voluntary disclosure programs, to manage enforcement costs and information problems.[13] In our paper, the firm may reduce the regulator's enforcement cost by committing to compliance through its investment in explainability and not by applying an ex-ante regulatory tool. Our paper provides practical guidance for curbing algorithmic-driven misconduct through auditing schemes that (indirectly) promote explainability.

[13] The theoretical literatures on leniency programs and on self-reporting are vast (seeMarvão and Spagnolo (2018) for a literature review on leniency and see, e.g., Kaplow and Shavell (1994), Innes (1999)

Finally, our paper contributes to the theoretical literature that studies how decisions to self-police are influenced by regulatory enforcement policy. Contrary to the literature on self-reporting, firms do not use regulatory mechanisms previously developed by public authorities; they self-regulate strategically to preempt future regulatory actions. Glazer and McMillan (1992) show theoretically that a monopolistic firm that faces the threat of regulation lowers its prices to avert regulation. Maxwell et al. (2000) study whether firms can avert environmental regulation by controlling pollution voluntarily. Suijs and Wielhouwer (2019) study coordination issues and free-riding problems when firms seek to avert regulation. Lyon and Maxwell (2016) characterise strategies deployed when firms signal their type through extensive self-regulation or remain in step with the rest of the industry through modest levels of self-regulation. Our model is closely related to that in Maxwell and Decker (2006), who investigate how a regulator may induce voluntary environmental investments. Contrary to Maxwell and Decker (2006), in our model the firm's investment facilitates regulatory audits. This generates additional strategic considerations for the firm and the regulator.

Much of the literature on industry self-regulation argues that firms can profitably preempt mandatory regulatory requirements (e.g., Short and Toffel (2010)). We show that this may not be the case when explainability facilitates audits. The regulator may strategically raise the frequency of its audits of explainable technologies where audits are more likely to be successful. This brings new insight how private investments that facilitate both private and public monitoring can be promoted.

3 The model

We consider a game with incomplete information between two strategic agents: a profit-maximising (risk-neutral) firm and a regulator. The firm uses a technology (the algorithm) that generates a fixed revenue but, with some probability, may also generate a net welfare cost $\kappa \geq 0$ to society. In this case, we say that the technology engages in "misconduct". The regulator seeks to minimize the technology's expected damage. He may audit the firm at frequency $m \in [0,1]$. If found guilty of misconduct, a fine $f \geq 0$ is imposed on the firm. To minimize the expected fine, the firm may endeavor to comply, as is reflected in a choice of compliance probability, or the probability that there is no misconduct, $\mathbf{p} \in [0,1]$. The compliance level $\mathbf{p}$ requires an effort cost $\epsilon(\mathbf{x},\mathbf{p})$, where $\mathbf{x} \in [0,1]$ is the explainability of the technology. The effort cost is an increasing and convex function of the compliance probability ($\epsilon_{\mathbf{p}} > 0$, $\epsilon_{\mathbf{pp}} > 0$). While the compliance level $\mathbf{p}$ is the firm's private information, the explainability level $\mathbf{x}$ is publicly observed. We assume the technology has a base explainability level $\mathbf{x}_0$, which is the technology's intrinsic explainability. Deviating from this base level generates a positive and convex cost $c(x)$, which finds its minimum in $\mathbf{x}_0$ ($c'(\mathbf{x}_0) = 0$, $c''(\mathbf{x}_0) > 0$).Explainability reduces the total as well as the marginal cost of compliance ($\epsilon_{\mathbf{x}} < 0$, $\epsilon_{\mathbf{xp}} < 0$). Crucially, we allow for explainability to affect the efficacy $\eta(\mathbf{x})$ of regulatory audits ($\eta'(\mathbf{x}) \geq 0$), which is the probability that the audit correctly identifies the misconduct.[14] In doing so, we explicitly acknowledge that explainability is a double-edged sword. It helps the firm ensure that its algorithm is compliant, but it may also make regulatory audits more efficacious. When $\mathbf{x} > \mathbf{x}_0$, there is investment in explainability. When $\mathbf{x} < \mathbf{x}_0$, there is obfuscation.

The firm chooses the explainability $\mathbf{x}$ of its technology and the compliance effort $\mathbf{p}$ to minimize its expected cost:

$$\min_{\mathbf{x},\mathbf{p}} L(\mathbf{x},\mathbf{p}) = c(\mathbf{x}) + \epsilon(\mathbf{x},\mathbf{p}) + (1-\mathbf{p})m\eta(\mathbf{x})f \tag{1}$$

The first two terms represent, in turn, the costs of providing $\mathbf{x}$ and $\mathbf{p}$. The last term corresponds to the expected fine. For simplicity, we assume that compliance efforts and audits occur before the technology is deployed in large-scale operations: the damage occurs if and only if neither the firm nor the regulator identifies technology misconduct. Thus, the expected social cost of the technology is $(1 - m\eta)(1 - \mathbf{p})\kappa$. In addition to minimizing the expected damage, the regulator is also concerned with its monitoring and enforcement cost, $\gamma(m)$, which is an increasing and convex function of the audit probability m ($\gamma_m > 0$ and $\gamma_{mm} > 0$). The regulator chooses its audit policy m to minimize the following objective function:[15]

$$\min_{m} C(m) = (1 - m\eta(\mathbf{x}))(1-\mathbf{p})\kappa + \gamma(m) \tag{2}$$

4 Benchmark: technology-neutral regulation

We first examine a benchmark case with "technology-neutral regulation", which means the regulator chooses a uniform rate of audit frequency for all technologies (i.e., regardless the explainability level). This case occurs when explainability is not observed prior to the audit. The firm chooses its explainability and effort levels $\mathbf{x}$ and $\mathbf{p}$, to minimize the expected costs of compliance (1) and, simultaneously, the regulator determines its audit frequency m to minimize (2). We assume that agents form rational expecta-

[14] For simplicity, we assume that the fine is conditional on the regulator's having proved the infringement: we allow only for type-2 errors (false negatives).

[15] In order to identify the tensions between firms and social interest as neatly as possible, this objective function is biaised against the firm. Including the firm's profits in the regulator's objective alters the quantitative results, but our main insights remain intact.

tions. As stated earlier, the regulator's ability to detect the technology misconduct may increase with explainability (i.e., $\eta'(\mathbf{x}) \geq 0$).[16] We obtain the following proposition:

Proposition 1 (technology-neutral regulation)**.** *With technology-neutral regulation, the equilibrium investment in explainability, compliance, and the probability that an audit occurs derive from the following relations:*

$$\epsilon_{\mathbf{x}} = -c'(\mathbf{x}) - \eta'(\mathbf{x})(1-\mathbf{p})mf \tag{3}$$

$$\epsilon_{\mathbf{p}} = m\eta(\mathbf{x})f \tag{4}$$

$$\gamma_m = (1-\mathbf{p})\eta(\mathbf{x})\kappa \tag{5}$$

Proof. Results from the differentiation of objective functions (1) with respect to $\mathbf{x}$ and $\mathbf{p}$, and (2) with respect to m. □

The first condition means that the explainability level is chosen such that the marginal benefit, which corresponds to the reduction in the cost of compliance, equals its marginal cost, which corresponds to the direct efficiency cost and the higher probability that the regulator finds a misconduct. The second condition means that the marginal cost of compliance equals the expected penalty for noncompliance. Finally, the third condition means that the regulator chooses its audit policy such that the marginal cost of regulation coincides with the marginal social benefit of detecting misconduct that the firm has not detected. Solving (3), (4), and (5) simultaneously and assuming rational expectations yields a Nash equilibrium solution for m, $\mathbf{p}$, and $\mathbf{x}$. We denote these as $\mathbf{x}^n$, $\mathbf{p}^n$, m^n, where the superscript n stands for "technology-neutral".

Lemma 1 describes the environments in which voluntary explainability or obfuscation may occur.

Lemma 1 (obfuscation or explainability)**.** *Firms make voluntary investments in explainability ($\mathbf{x}^n > \mathbf{x}_0$) if and only if*

$$(1-\mathbf{p})\frac{\eta'(\mathbf{x}^n)}{\eta(\mathbf{x}^n)} \cdot \frac{\epsilon_{\mathbf{p}}(\mathbf{x}^n, \mathbf{p}^n)}{-\epsilon_{\mathbf{x}}(\mathbf{x}^n, \mathbf{p}^n)} < 1 \tag{6}$$

Otherwise, they engage in obfuscation ($\mathbf{x}^n < \mathbf{x}_0$).

Proof. Lemma 1 derives immediately from (3) and (4), and the observation that voluntary investments corresponds to situations in which $c'(x) > 0$, which is equivalent to $x > x_0$. Obfuscation corresponds to situations in which $c'(x) < 0$ $(x < x_0)$ □

[16] The particular case where $\eta(\mathbf{x}) = 1$ for all $\mathbf{x}$ coincides in our model with a setting where the firm (and not the regulator) would bear the burden of the proof, in case of an audit.

Recalling that audit efficacy $\eta(\mathbf{x})$ is a primitive of the model, this lemma can be reformulated as follows: if explainability strongly affects audit accuracy $\eta(\mathbf{x})$ but does not significantly reduce compliance costs $\epsilon(\mathbf{x}^n, \mathbf{p})$ much, firms will engage in obfuscation. The following corollary describes an interesting special case where the firm never invests in explainability and evades regulatory oversight.

Corollary 1 (black-box algorithms)**.** *If the regulator cannot detect misconduct in a base technology, there is no investment in explainability and no investment in compliance.*

Proof. Using Proposition 1 with $\eta(\mathbf{x}_0) = 0$, the unique equilibrium is $\mathbf{x}^n = \mathbf{x}_0$, $\mathbf{p}^n = m^n = 0$. □

This simple result rationalises the commonly observed empirical fact that machine-learning algorithms are black boxes over which regulators currently have little power. This allows firms to hide misconduct behind opaque algorithms. If such a case occurs, a minimum explainability standard (MES) should be considered.

Corollary 2 (command-and-control regulation)**.** *When explainability strongly increases the efficacy of regulatory audits, there is no voluntary investment in explainability. If implemented, the minimum explainability standard $\underline{\mathbf{x}}$ determines the level of technology explainability.*

Proof. Assume there exists a minimum explainability standard $\underline{\mathbf{x}} \geq \mathbf{x}_0$. If

$$\epsilon_{\mathbf{x}}(\underline{\mathbf{p}}, \underline{\mathbf{x}}) + c'(\underline{\mathbf{x}}) + \eta'(\underline{\mathbf{x}})(1 - \underline{\mathbf{p}})\underline{m} f > 0,$$

with $\underline{\mathbf{p}}$ and $\underline{m}$ derived from (4) and (5) evaluated in $\mathbf{x} = \underline{\mathbf{x}}$, then the only equilibrium is $\mathbf{x}^n = \underline{\mathbf{x}}$, $\mathbf{p}^n = \underline{\mathbf{p}}$ and $m^n = \underline{m}$. □

Appendix 1.A proposes an application of the results of this section to standard cost functions. Corollaries 1 and 2 describe the rather unfavourable case in which audit efficacy is low and strongly affected by explainability. When, instead, Condition (6) is met, voluntary investment rises ($\mathbf{x}^n > \mathbf{x}_0$) with the equilibrium variables described in Proposition 1. In the next section, we propose the technology-specific regulation that, in some cases, further promotes explainability and compliance.

5 Technology-specific regulation

In this section, we modify the timing of the game to allow the regulator to observe the explainability level $\mathbf{x}$ before choosing its audit policy. This situation would emerge if firms are mandated to disclose some of the characteristics of their decision-making processes, so regulators may infer their explainability prior to conducting the audit. This allows for technology-specific regulation, in which the regulator designs an audit frequency policy that depends on the observed level of explainability. The timing plays out in two stages:

- Stage 1: The firm invests in explainability $\mathbf{x}$, which is observed publicly.
- Stage 2: The firm chooses its privately observed compliance probability $\mathbf{p}$ and, simultaneously, the regulator chooses the audit frequency m.

We look for the subgame perfect Nash equilibrium of this game. Following standard backward-induction logic, the analysis starts in the last stage of the game and proceeds from there. We may denote variables of this section with a superscript s, which stands for "specific". It denotes variables related to the setting with technology-specific regulation.

Stage 2

The firm selects its effort $\mathbf{p}$ to minimize its costs (1), given rationally anticipated audit frequency $m(\mathbf{x})$ and, simultaneously, the regulator determines its audit frequency m to minimize (2), given rationally anticipated audit frequency $\mathbf{p}(\mathbf{x})$. This leads in equilibrium to the following relations, much like in equations (4) and (5):

$$\epsilon_{\mathbf{p}} = m(\mathbf{x})\eta(\mathbf{x})f \tag{4'}$$

$$\gamma_m = \kappa(1-\mathbf{p}(\mathbf{x}))\eta(\mathbf{x}) \tag{5'}$$

The interpretation of these two equations is similar to that of the benchmark. The difference is that the decision variables $\mathbf{p}$ and m, now depend explicitly on explainability $\mathbf{x}$. We denote $\mathbf{p}^s(\mathbf{x})$, $\mathbf{m}^s(\mathbf{x})$ as the solutions to (4') and (5'). By implicit differentiation of $m^s(\mathbf{x})$ and $\mathbf{p}^s(\mathbf{x})$ with respect to $\mathbf{x}$, we obtain the following relations:

$$m^s_{\mathbf{x}} = \frac{\epsilon_{\mathbf{xp}}\kappa\eta + \eta_{\mathbf{x}}\kappa\Big((1-\mathbf{p})\epsilon_{\mathbf{pp}} - m\eta f\Big)}{\kappa f\eta^2 + \gamma_{mm}\epsilon_{\mathbf{pp}}} \tag{7}$$

$$\mathbf{p}^s_{\mathbf{x}} = \frac{-\epsilon_{\mathbf{xp}}\gamma_{mm} + \eta_{\mathbf{x}} f\left((1-\mathbf{p})\kappa\eta + m\gamma_{mm}\right)}{\kappa f\eta^2 + \gamma_{mm}\epsilon_{\mathbf{pp}}} \tag{8}$$

The first term of the numerator in both equations represents the "commitment to comply" that stems from explainability. This increases compliance (Equation 8), as a marginal increase in explainability decreases the marginal cost of compliance ($\epsilon_{\mathbf{xp}} < 0$). This also tends to decrease audit pressure in Equation (7), as regulators rationally anticipate that higher explainability generates greater compliance. The second term in the numerator in both equations represents the "opportunistic auditing policy" effect of explainability. This effect always increases compliance but has ambiguous effects on the auditing policy. On the one hand, a regulator may strategically audit firms with higher explainability, as doing so makes more likely audit success. This effect is captured by the term $(1-\mathbf{p})\epsilon_{\mathbf{pp}}$. On the other hand, high audit accuracy makes actual auditing less necessary as the trigger of an effective response by the firm. This effect is captured by the term $m\eta f$.

Stage 1

In Stage 1, the firm chooses explainability by rationally anticipating $\mathbf{p}^s(\mathbf{x})$ and $m^s(\mathbf{x})$. We rewrite the objective function (1):

$$\min_{\mathbf{x},\mathbf{p}} L(\mathbf{x},\mathbf{p}) = c(\mathbf{x}) + \epsilon(\mathbf{x},\mathbf{p}^s(\mathbf{x})) + (1-\mathbf{p}^s(\mathbf{x}))m^s(\mathbf{x})\eta(\mathbf{x})f \tag{1'}$$

Recalling from the resolution of the second stage that in equilibrium $\epsilon_{\mathbf{p}}(\mathbf{x}^s,\mathbf{p}^s) = m^s(\mathbf{x}^s)f\eta(\mathbf{x}^s)$, we obtain an implicit formulation of the firm's equilibrium investment in explainability, $\mathbf{x}^s$:

$$c'(\mathbf{x}) = -\epsilon_{\mathbf{x}} - (1-\mathbf{p}^s)f\left(\eta'(\mathbf{x})m^s + \eta m^s_{\mathbf{x}}\right) \tag{3'}$$

This expression is the technology-specific counterpart of equation (3). We summarise these findings in the following proposition

Proposition 2 (technology-specific regulation)**.** *With technology-specific regulation, the equilibrium investment in explainability, compliance, and audits derive from Equations (3'), (4') and (5').*

Proof. Derives from previous developments. □

From Proposition 2, we derive the following corollary:

Corollary 3 (audits unaffected by explainability)**.** *When explainability does not affect the quality of audits, i.e., $\eta'(\mathbf{x}) = 0$, the adoption of a technology-specific regulation always favors explainability and compliance.*

Proof. See Appendix 1.B.1. $\square$

In this scenario, the only effect of explainability on regulatory audits is the "commitment to comply": explainability allows the firm to use its investment in explainability as a signalling and commitment device to signal its compliance efforts. Because this effect reduces the likelihood that it incurs an audit, the firm raises its investment in explainability relative to the equilibrium investment under technology-neutral regulation ($i.e., \mathbf{x}^s > \mathbf{x}^n$).

As we noted with regard to the benchmark of Section 4, however, the explainability of machine-learning techniques strongly affects the efficacy of audits. This may affect the relative efficacy of technology-neutral and technology-specific regulations, as we show in Lemma 2 and Corollary 4:

Lemma 2 (technology-neutral or technology-specific regulation)**.** *Technology-specific regulation induces more explainability and compliance than technology-neutral regulation if and only if:*

$$\frac{\eta'(\mathbf{x}^s)}{\eta(\mathbf{x}^s)} \cdot \frac{1}{-\epsilon_{\mathbf{xp}}(\mathbf{x}^s, \mathbf{p}^s)} \Big((1 - \mathbf{p}^s)\epsilon_{\mathbf{pp}}(\mathbf{x}^s, \mathbf{p}^s) - \epsilon_{\mathbf{p}}(\mathbf{x}^s, \mathbf{p}^s) \Big) < 1 \tag{9}$$

Proof. The proof notes, based on (3'), that technology-specific regulation induces higher explainability and compliance than technology-neutral regulation if and only if $m^s_{\mathbf{x}}(\mathbf{x}^s) < 0$ (see Lemma 3 in Appendix 1.B.2). Inserting (4') in (7), we obtain condition (9). $\square$

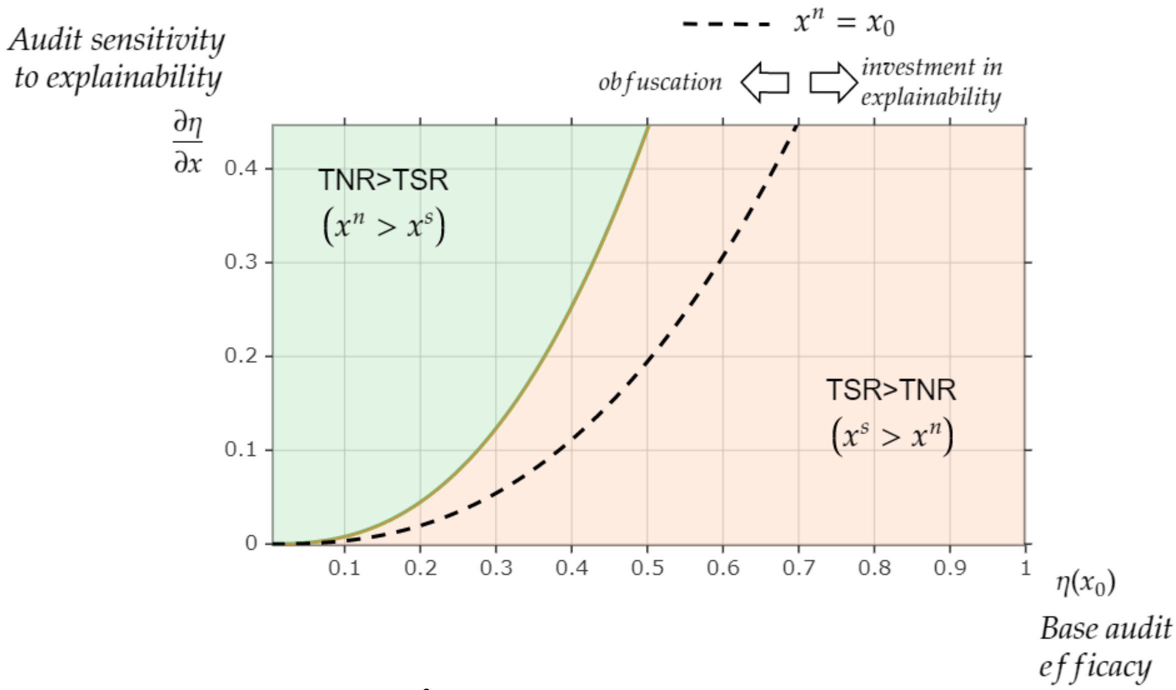
Corollary 4 (regulatory opportunism)**.** *When the fine f is small, explainability strongly affects the quality of audits ($\eta'(\mathbf{x})$ is large) and does not strongly affect the cost of compliance ($\epsilon_{\mathbf{xp}}$ is small), technology-neutral regulation induces more robust investment in explainability and compliance than technology-specific regulation.*

Proof. See Appendix 1.B.2. $\square$

The effect of technology-specific regulation on explainability is ambiguous. It depends on the sign of $m^s_{\mathbf{x}}$. If the opportunistic regulatory response dominates the commitment effect ($m^s_{\mathbf{x}} > 0$), explainability facilitates inspection by the regulator: the firm lowers its investment in explainability relative to that investment under technology-neutral regulation. Conversely, if ($m^s_{\mathbf{x}} < 0$), technology-specific regulation promotes explainability.

Figure 1 illustrates the results derived from Proposition 1 and indicates how they compare with those derived from Proposition 2 based on the specification detailed in Appendix 1.A. We observe that, when audit accuracy is low and highly sensitive to explainability ($\eta(\mathbf{x}_0)$ is small and $\eta'(\mathbf{x}_0)$ is large) , firms are more likely to engage in obfuscation, and technology-neutral regulation should be preferred over technology-specific regulation.

Figure 1: Obfuscation, explainability and best regulatory regimes as a function of audit efficacy



Graph drawn for $\epsilon(\mathbf{x},\mathbf{p}) = \frac{\mathbf{p}^2}{1+\mathbf{x}}$, $c(\mathbf{x}) = (\mathbf{x}-\mathbf{x}_0)^2$, with $\mathbf{x}_0 = 1$, and $\gamma(m) = \frac{m^2}{2}$. Audit efficacy is linear in $\mathbf{x}$: $\eta(\mathbf{x}) = max(0, \eta(\mathbf{x}_0) + b(\mathbf{x}-\mathbf{x}_0))$. The area to the northwest of the dotted line corresponds to settings where there is obfuscation under technology-neutral regulation. The area to the southeast represents settings where there is voluntary investment in explainability.

To promote explainability under technology-specific regulation, the regulator should make a credible commitment to eschewing opportunism. A possible solution is that the legislator modifies the regulator's objective function (2) so it does not explicitly depend on $\eta(\mathbf{x})$.

6 Conclusion and policy implications

Our analysis has highlighted an important trade-off that firms contemplating investment in explainability face: the firm in our model may choose either to invest in explainability and take advantage of a reduction in compliance costs or strategically reduce explainability and reduce the regulatory pressure it experiences. This decision depends crucially on the regulatory framework in which it operates.

When explainability strongly affects the efficacy of regulatory audits, firms may strategically reduce explainability or even actively obfuscate their technology processes to render audits ineffective. This results in very low levels of compliance. In this case, minimum explainability standards may need to be deployed. When explainability does not strongly affect audit efficacy, some degree of self-policing may be observed. When the regulator adopts a technology-specific regulation, explainability acts as a signalling and commitment device the firm uses to signal compliance efforts. This tends to reduce regulatory pressure and increase explainability, as it helps the firm reduce compliance costs significantly. However, when explainability affects audit efficacy, another factor is regulatory opportunism that deters investment in explainability. When this effect dominates, technology-neutral regulation must be envisaged. This calls for a careful design of explainability regulatory policy.

In addition, leniency and voluntary disclosure programs can be used in parallel with regulatory explainability policy. They can be particularly useful in addressing new AI technologies. These tools provide incentives, such as immunity or reduced enforcement, to those who report voluntarily while providing regulators with valuable information on existing risks and areas of non-compliance.

Our work could be extended in at least two directions. First, we deliberately chose a setting where the regulator bears the burden of the proof. It is important to note that making the responsibility of firms to demonstrate their innocence would enhance incentives for explainability and technology-specific regulation would unambiguously strengthen these incentives. Second, we assume the regulator and firms' audit technologies are independent. Allowing for correlation may highlight interesting signalling effects. The effect of initiatives such as leniency programs could also be studied.

Appendix

1.A An application

We now propose an application of our model. Assume that the firm's costs of compliance is $\epsilon(\mathbf{x},\mathbf{p}) = \frac{\mathbf{p}^2}{\mathbf{x}+a}$ with $a > 0$. The firm's cost of explainability is $c(\mathbf{x}) = \frac{\mathbf{x}^2}{2}$. This means that the base explainability is $\mathbf{x}_0 = 0$. Finally, the regulator monitoring cost is $\gamma(m) = \frac{m^2}{2}$.

1.A.1 No explainability

The first-order condition for explainability (3) can be rewritten as:

$$A(\mathbf{x}) = \mathbf{x} + \eta'(\mathbf{x})mf(1-\mathbf{p}) - \frac{\mathbf{p}^2}{(\mathbf{x}+a)^2}$$

Assume further for simplicity that $\frac{\partial A(\mathbf{x})}{\partial \mathbf{x}} > 0$ so the firm's cost-minimizing exercise has an interior solution. It suffices for example to impose the condition that $\eta_{\mathbf{xx}}$ not be too negatively large. We have that

$$A(0) = \eta'(0)mf(1-\mathbf{p}) - \frac{\mathbf{p}^2}{a^2} \tag{10}$$

Assume that $\eta'(0) = 0$ or that $\eta'(0)$ and $\mathbf{p}$ is large enough.[17] We have that $A(0) < 0$ and $A(+\infty) > 0$. As $A(\mathbf{x})$ is always continuous and differentiable, there exists a positive level of explainability, $\mathbf{x}^* > 0$, such that $A(\mathbf{x}^*) = 0$: self-policing emerges, even in the absence of a minimum explainability standard, when $\eta^2(0)f$ is large enough. Failing these conditions, $A(0) > 0$ and there is obfuscation: $\mathbf{x}^n < 0$.

1.A.2 Explainability or obfuscation?

If $\mathbf{x}^n > 0$, firms make their algorithms explainable. If $\mathbf{x}^n < 0$ they obfuscate them. In equilibrium, solving (4) and (5) allows us to set $\mathbf{p}$ and m:

$$m = \frac{2\kappa\eta(\mathbf{x})}{2 + (\mathbf{x}+a)\kappa f \eta(\mathbf{x})^2}$$

[17] The latter outcome occurs when the regulator's ability to detect technological misconduct in the absence of explainability and the fine are sufficiently large (i.e., $f\eta(0)^2 \gg 0$).

$$\mathbf{p} = \frac{(\mathbf{x}+a)\kappa f\eta(\mathbf{x})^2}{2+(\mathbf{x}+a)\kappa f\eta(\mathbf{x})^2}$$

The equilibrium explainability $\mathbf{x}^n$ is then derived from (3):

$$\mathbf{x}^n = \mathbf{x}_0 + \frac{\eta(\mathbf{x}^n)\kappa f}{(2+\eta^2(\mathbf{x}^n)\kappa f(\mathbf{x}^n+a))^2}\left(\eta^3(\mathbf{x}^n)\kappa f - 2\eta'(\mathbf{x}^n)\right) \tag{11}$$

We conclude that, if $\eta^3(\mathbf{x}^n)\kappa f > 2\eta'(\mathbf{x}^n)$, firms invest in explainability ($\mathbf{x}^n > \mathbf{x}_0$). Otherwise, they obfuscate their algorithms ($\mathbf{x}^n < \mathbf{x}_0$). Recalling that $\eta(\mathbf{x})$ is a primitive of the model, this conclusion can be reformulated as follows: when the fine and audit accuracy are too low relative to the sensitivity of audit accuracy to explainability, firms strategically make their algorithms less transparent.

1.B Technology-specific regulation

1.B.1 Explainability does not affect audit efficacy

Recall that $\epsilon_{\mathbf{px}} < 0, \epsilon_{\mathbf{pp}} > 0$. When audit efficacy does not depend on explainability (i.e., $\eta_{\mathbf{x}} = 0$), we derive the following results by applying the implicit function theorem to (4') and (5') and solving for $m_{\mathbf{x}}^{s*}$ and $\mathbf{p}_{\mathbf{x}}^{s*}$:

$$m_{\mathbf{x}}^{s*} = \frac{\kappa\eta\epsilon_{\mathbf{px}}}{cf\eta^2 + \gamma_{mm}\epsilon_{\mathbf{pp}}} < 0 \tag{12}$$

$$\mathbf{p}_{\mathbf{x}}^{s*} = \frac{-\epsilon_{\mathbf{xp}}\gamma_{mm}}{cf\eta^2 + \gamma_{mm}\epsilon_{\mathbf{pp}}} > 0 \tag{13}$$

We define the equilibrium investment as $\mathbf{x}^{s*}$, which is the solution to this equation:

$$\epsilon_{\mathbf{x}} = -c_{\mathbf{x}} - (1-\mathbf{p}^{s*})\eta f m_{\mathbf{x}}^{s*} > 0 \tag{14}$$

We now follow the proof derived in Maxwell and Decker (2006), Proposition 1(B). As the authors notice, we cannot generally compare equilibrium investment between unresponsive and responsive regulation directly because doing so involves making comparisons across two separate models. Following Brander and Spencer (1983), though, we can make such a comparison. The proof makes use of the mean value theorem. Let $f(x)$ be a continuously differentiable function defined over the set of real numbers R^2 and let x^* and x^n be two points on this function. Then there exists a point

x^c such that

$$\Delta f = f(x^{s*}) - f(x^n) = \frac{\partial f}{\partial x}|_{x=x^c}(x^{s*} - x^n) \tag{15}$$

where $x^c = x^n + \theta(x^{s*} - x^n)$ and $\theta \in (0,1)$.

Using this theory, we first define $\Delta \mathbf{x} = \mathbf{x}^{s*}$, where $\mathbf{x}^{s*}$ and $\mathbf{x}^n$ are investments in explainability in the responsive and unresponsive cases, respectively. Let $f(x)$ be $\frac{E^{s*}(C)}{\partial \mathbf{x}}$ for both $\mathbf{x}^{s*}$ and $\mathbf{x}^n$. We then apply 15 as follows (dropping the C argument for notational convenience):

$\Delta \frac{\partial E^{s*}}{\partial \mathbf{x}} = \frac{\partial E^{s*}}{\partial \mathbf{x}}|_{\mathbf{x}=\mathbf{x}^{s*}} - \frac{\partial E^{s*}}{\partial \mathbf{x}}|_{\mathbf{x}=\mathbf{x}^n} = \frac{\partial^2 E^{s*}}{\partial \mathbf{x}^2}|_{\mathbf{x}=\mathbf{x}^c}(\mathbf{x}^{s*} - \mathbf{x}^n)$ Re-arranging terms we can get

$$(\mathbf{x}^{s*} - \mathbf{x}^n) = \frac{\frac{\partial E^{s*}}{\partial \mathbf{x}}|_{\mathbf{x}=\mathbf{x}^{s*}} - \frac{\partial E^{s*}}{\partial \mathbf{x}}|_{\mathbf{x}=\mathbf{x}^n}}{\frac{\partial^2 E^{s*}}{\partial \mathbf{x}^2}|_{\mathbf{x}=\mathbf{x}^c}} \tag{16}$$

From (14) we know that $\frac{\partial E^{s*}}{\partial \mathbf{x}}|_{\mathbf{x}=\mathbf{x}^{s*}} = 0$ and $\frac{\partial E^{s*}}{\partial \mathbf{x}}|_{\mathbf{x}=\mathbf{x}^n} < 0$. Therefore, the numerator in (16) is positive. Since cost minimization requires that $\frac{\partial^2 E^{s*}}{\partial \mathbf{x}^2}|_{\mathbf{x}=\mathbf{x}^c} > 0$, we can conclude that $(\mathbf{x}^{s*} - \mathbf{x}^n) > 0$. As Brander and Spencer (1983) note, existence and uniqueness are difficult to establish in stage games, so second-order partials derived from such games are difficult to sign in practice. In our case, we find that, when we expand the equation,

$\frac{\partial^2 E^{s*}}{\partial \mathbf{x}^2}|_{\mathbf{x}=\mathbf{x}^c} = \epsilon_{\mathbf{xx}} - \frac{\partial m^{s*}}{\partial \mathbf{x}}\frac{\partial \mathbf{p}^{s*}}{\partial \mathbf{x}} f + (1 - \mathbf{p}^{s*}) f \frac{\partial^2 m^{s*}}{\partial \mathbf{x}^2}$

Note that the first two terms in this equation are positive, which works towards the cost-minimizing result, but the third term is indeterminate because $\frac{\partial^2 m^{s*}}{\partial \mathbf{x}^2}$ cannot, in general, be signed. However, straightforward differentiation shows that each component of $\frac{\partial^2 m^{s*}}{\partial \mathbf{x}^2}$ involves third-order cross partial derivatives from our $\epsilon(\mathbf{x}, \mathbf{p})$ function. As a result $\frac{\partial^2 m^{s*}}{\partial \mathbf{x}^2}$ is ambiguous. In practice, such third -and higher- order effects are reasonably assumed to be relatively small. Because the first two terms in the preceding equation are higher-order effects of the correct sign, we follow Brander and Spencer (1983) and reasonably conclude that, overall, $\frac{\partial^2 m^{s*}}{\partial \mathbf{x}^2} < 0$.

1.B.2 Explainability affects audit efficacy

We first prove the following Lemma:

Lemma 3. *Technology-specific regulation induces greater compliance and explainability than technology-neutral regulation if and only if explainability induces less robust audit efforts by the regulator ($m^s_{\mathbf{x}} < 0$).*

Proof. The proof follows from the comparison of (3) and (3'). □

Recall that $\epsilon_{\mathbf{xp}} < 0$, $\epsilon_{\mathbf{pp}} > 0$. When explainability affects audit efficacy (i.e., $\eta_{\mathbf{x}} > 0$), a second term in the numerator of the two best response functions is added, in contrast to (12) and (13):

$$\mathbf{p}_{\mathbf{x}}^{s} = \frac{-\gamma_{mm}\epsilon_{\mathbf{xp}} + f\eta_{\mathbf{x}}\left((1-\mathbf{p})c\eta + m\gamma_{mm}\right)}{cf\eta^2 + \gamma_{mm}\epsilon_{\mathbf{pp}}} > 0 \tag{17}$$

$$m_{\mathbf{x}}^{s} = \frac{\kappa\eta\epsilon_{\mathbf{px}} + c\eta_{\mathbf{x}}\Big((1-\mathbf{p})\epsilon_{\mathbf{pp}} - m\eta f\Big)}{cf\eta^2 + \gamma_{mm}\epsilon_{\mathbf{pp}}} \lesseqgtr 0 \tag{18}$$

Following a marginal increase in explainability, we see that:

- The increase in compliance effort is always higher with technology-specific regulation ($\mathbf{p}$ increases in $\eta_{\mathbf{x}}$), as the second term of the numerator in Equation (17) is always positive.
- Audit frequency may decrease when the expected fine is larger than the expected marginal compliance cost ($(1-\mathbf{p})\epsilon_{\mathbf{pp}} < m\eta f$).

1.C The social planner

A social planner tries to maximize the benefit of the technology and limits its damage. He is also concerned about the audit and enforcement costs of the regulator, $\gamma(m)$, and about the firm's explainability and compliance costs $c(\mathbf{x})$ and $\epsilon(\mathbf{x},\mathbf{p})$. The social planner's objective is then given by:

$$\min_{\mathbf{x},\mathbf{p},m} S(\mathbf{x},\mathbf{p},m) = c(\mathbf{x}) + c(1-\mathbf{p})(1-\eta(\mathbf{x})m) + \epsilon(\mathbf{x},\mathbf{p}) + \gamma(m)$$

Table 1.C.1 compares the outcomes of a social planner who could control all strategic variables and the outcomes of the two regulatory regimes considered in the paper.

Social planner	Technology-neutral regulation	Technology-specific regulation
$\epsilon_{\mathbf{x}} = -c'(\mathbf{x}) + \kappa(1-\mathbf{p})m\eta_{\mathbf{x}}$	$\epsilon_{\mathbf{x}} = -c'(\mathbf{x}) - (1-\mathbf{p})fm\eta'(\mathbf{x})$	$\epsilon_{\mathbf{x}} = -c'(\mathbf{x}) - (1-\mathbf{p})f\left(\eta'(\mathbf{x})m + \eta m_{\mathbf{x}}\right)$
$\epsilon_{\mathbf{p}} = \kappa(1-\eta(\mathbf{x})m)$	$\epsilon_{\mathbf{p}} = m\eta(\mathbf{x}f)$	$\epsilon_{\mathbf{p}} = m(\mathbf{x})\eta(\mathbf{x})f$
$\gamma_m = \kappa(1-\mathbf{p})\eta(\mathbf{x})$	$\gamma_m = \kappa(1-\mathbf{p})\eta(\mathbf{x})$	$\gamma_m = \kappa(1-\mathbf{p})\eta(\mathbf{x})$

Table 1.C.1: First-order conditions in first-best (left), technology-neutral (center) and technology-specific regulation (right)

A few observations are in order. First, as expected, the social planner chooses its audit level in the same way as the regulator in both regulatory regimes.

Second, the social planner chooses a compliance effort such that the cost of the marginal compliance effort corresponds to the damage cost, while the company chooses its compliance effort in accordance with its expectation of a fine.

Third, the social planner chooses its level of investment in explainability such that the marginal social benefit, which is the reduction in the compliance effort cost and the increase in audit efficacy, equals the loss of technology efficiency. Instead, the firm weights the benefits of explainability against its direct costs and the increased likelihood of a successful audit. We observe that, in both regulatory regimes, explainability is too low relative to the first best.

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Chapter 2

Platform coopetition in two-sided markets

1 Introduction

Platforms are intermediaries that facilitate interaction between distinct groups of users. The benefit enjoyed by a member of one group depends on how well the platform enables him to interact with members of the other group. Positive cross-group network effects are the main source of value creation and competitive advantage for platforms. The presence of network effects leads some users to multihome (i.e., subscribe to several platforms) to enjoy interactions with as many users as possible on the other side of the market. This situation appears in the so-called competitive bottleneck in which participants in one group choose at most one platform (i.e., singlehome), while participants in the other group can choose to be active on both platforms (i.e., multihome). Multihoming benefits not only users who multihome, by interacting with a larger set of users of the other group, but also users of the other side of the platform who have the possibility to interact with additional participants.
However, because the benefits of network effects are allocated through different intermediaries, each platform may not fully internalise the surplus generated by such practices. One approach to improve the management of network effects by platforms would be to allow them to cooperate on the instruments that affect multihoming. One of these instruments is the subscription price paid by users to join the platform. However, cooperation on price between competitors may be problematic from a regulatory and efficiency perspective. To safeguard the benefits from cooperation and, at the same time, ensure a competitive environment, platforms should continue to compete on other strategic variables. We refer to such situations as “coopetition”.

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Several examples of coopetition have been studied in the context of "traditional markets" (i.e., one-sided markets), such as R&D joint ventures or patent pools. Patent pools are joint marketing agreements in which patent holders jointly sell their licenses as in bundles through a joint subsidiary and fix a common price for this bundle. The economic rationale behind the regulatory acceptance of patent pools is to allow patent holders to take into account patent complementarity for users in their pricing decision and consequently solve Cournot's double marginalisation problem.

However, it is not obvious that the analysis of cooperation in "traditional" markets can be easily extended to two-sided markets. There is evidence of platforms being convicted of coordinating only on one side of the market. For example, competition authorities have sanctioned several cases of price semi-collusion in the media sector.[1] Recently, the French Competition Authority sanctioned a practice of price semi-collusion in a two-sided competitive bottleneck market in the French market for luncheon vouchers.[2] The issuers of meal vouchers ("the platforms") exchanged information leading to complete coordination on the commission fees paid by merchants ("the multihoming side") while competing to attract employers buying meal vouchers for their employees ("the single-homing side").[3]

Recent research suggests that in some contexts, such practices increase total welfare.[4] Moreover, there have been policy proposals to allow coopetition strategies in two-sided markets.[5]

The purpose of this article is to study the price and welfare effects of one-sided price coordination between two horizontally differentiated platforms in a bottleneck environment, with or without the possibility of demand expansion.

We assume that cooperation between platforms occurs on the multihoming side (e.g., the seller side). We then compare this coopetition situation to a benchmark situation where platforms compete on both sides. In the coopetition scenario, platforms cooperatively set the price for sellers to maximise their joint profits and non-cooperatively set the price for buyers to maximise their individual profits. We compare these two different environments in a "mature market", in which the total number of buyers is fixed, and in

[1] See Lefouili and Pinho (2020) and Dewenter et al. (2011).

[2] See Case n°19-D-25 of the French Competition Authority. This meal voucher is a form of payment allowing employees who benefit from it to pay the price of a meal or for certain food products that can be used in the composition of a meal.

[3] Although the issuers attempted to restrict competition between them, competition was still effective on that side of the market.

[4] See Lefouili and Pinho (2020) and Dewenter et al. (2011)

[5] As reported by Dewenter et al. (2011), in Germany, a policy suggestion for policy intervention has been to allow newspapers to cooperate in advertising markets while competing in reader markets. In Germany, some newspapers have already established separate firms ("Anzeigengemeinschaft") that handle ad management on their behalf. Often, however, the firms in an "Anzeigengemeinschaft" belong to a single owner (e.g., Zeitungsgruppe Stuttgart).

a "market with demand expansion", where platforms can expand their customer base on the buyer side.[6]

In a bottleneck situation, sellers can join both platforms. Therefore, platforms do not compete directly to attract them. By contrast, buyers have to choose which platform to join. Platforms compete for them by using two instruments: the buyers' subscription price and the presence of sellers, which generates network effects on buyers. In the presence of positive network effects, we find that under coopetition, coordination on the seller side drives platforms to set higher subscription prices for sellers, even higher than the monopoly price. Indeed, coordination allows platforms to internalise that when they reduce their price for sellers, this harms the rival platform by making it less attractive to buyers. Internalising this effect makes platforms charge higher fees to sellers. However, as sellers become more valuable, the competition for buyers is intensified, and platforms therefore charge lower fees to buyers under coopetition. Therefore, the effect of coopetition on platforms is a priori ambiguous, as the subscription price increases on one side but decreases on the other side. The same is true for users. Surprisingly, under some circumstances, the competition to attract buyers may be so intense that platforms prefer competition rather than coopetition. In a mature market, coopetition always decreases total surplus, whereas in a market with demand expansion, total welfare can increase.

The remainder of the paper is organised as follows. In Section 2, we review the literature. In Section 3, we describe the model and users' subscription decisions. In 4, we analyse the case of coopetition in a mature market, and in Section 5, we analyse the case with demand expansion. In Section 6, we conclude the paper.

2 Literature review

Our paper is related to the theoretical literature on semi-collusion that studies the welfare effects of situations where firms cooperate (or collude) in one dimension but compete in at least one other dimension. This type of strategy has been widely studied in the context of one-sided markets with cooperation in R&D (d'Aspremont and Jacquemin (1988)), capacity (Osborne and Pitchik (1987)), or quality (Foros et al. (2002)). This literature shows that semi-collusion may be profitable and efficient under certain circumstances, usually because problems resulting from over-investment in R&D, qual-

[6] The "mature market" and "the market with demand expansion" are not quantitatively comparable. The size of the mature market is set to 1 (which is the length of the linear city interval), but the size of the growing market is larger.

ity or capacity or inefficient product differentiation are resolved (see, e.g., Brod and Shivakumar (1999)). However, semi-collusion is not always profitable and can be inefficient (see, e.g., Fershtman and Gandal (1994)).
The theoretical literature on semi-collusion in the context of two-sided markets is scarcer. Using a representative consumer approach, Dewenter et al. (2011) show that semi-collusion can improve total welfare in two-sided markets. They consider a static setting in which newspapers (i.e., platforms) compete on price in the reader market and on quantity in the advertising market and compare the welfare impacts of one-sided perfect collusion on the advertising side and two-sided competition. They find that when newspapers collude on the advertiser side, the price is lower on the non-cooperative side and higher on the collusive side than the static Nash prices. In their setting, semi-collusion can increase total surplus and even be a Pareto improvement in the sense that all players gain.
While our results are similar to those of Dewenter et al. (2011), we investigate the welfare effects of semi-collusion in the competitive bottleneck framework developed by Armstrong (2006). We use a slightly modified version of this seminal model with an endogenisation of the multihoming decision of users proposed by Armstrong and Wright (2007). Ruhmer (2011) considers a repeated version of the two-singlehoming Armstrong model to study the incentives of platforms to perfectly collude on one side of the market and two sides of the market. Lefouili and Pinho (2020) extend this paper by allowing for intermediate degrees of collusion and consider a competitive bottleneck environment.
Focusing on the multihoming bottleneck environment in a static game with positive network effects, we show that some results of Lefouili and Pinho (2020) are more likely to hold when there is demand expansion on the competitive side (e.g., the buyer side in our setting). To model demand expansion, we use the Hotelling model with hinterlands (Armstrong and Wright (2009), Hagiu and Lee (2011), Choi et al. (2012)). Finally, the structure of our paper is close to that of Belleflamme and Peitz (2019). Their paper explores the allocative effects of a change from singlehoming to multihoming. In contrast, we explore the allocative effects of a change in users' demand structure (i.e., with and without demand expansion) but also a change in platforms' strategy (i.e., from competition to coopetition).
This paper contributes to the important policy debate that attempts to analyse under which conditions cooperation between firms can increase total welfare. Our main finding is that cooperation is more likely to increase total welfare in a two-sided market with the possibility of demand expansion than in a mature market.

3 Model

Users' utility functions Following Armstrong (2006), we assume that two symmetric platforms facilitate the interaction between two groups of users: sellers and buyers. Buyers purchase one unit of a perfectly differentiated product offered by each active seller on the platform. Each trade generates a benefit α_B for the buyer and a benefit α_S for the seller. Sellers and buyers also derive stand-alone benefits from joining a platform, denoted by β_S and β_B, respectively. In terms of stand-alone benefits, we assume that the two platforms provide completely differentiated benefits such that a multihoming seller obtains β_S on each platform.

Each platform $i \in \{1,2\}$ incurs constant marginal costs to serve sellers and buyers (c_S, c_B) and charges them a subscription price (p_S^i, p_B^i) to access the service. Sellers can multihome (i.e., be active on both platforms), while buyers singlehome (i.e., they are active on only one platform). Users perceive platforms as horizontally differentiated *à la Hotelling*. We consider only cases in which the market is covered, i.e., all users participate. Sellers and buyers are uniformly distributed along a unit interval, and platforms are located at the extremes. We assume that platform 1 is located on the left and platform 2 on the right of the unit interval. To model the elastic participation of buyers, we add captive buyers on each side of the unit interval that can be considered the "hinterlands" of each platform.[7] These captive buyers never consider buying from the alternative platform because they have strong horizontal preferences. This assumption reflects a real-world environment in which some platforms have strong market power over users because of the lack of competition for their "captive buyers", while their market power is limited with respect to users who can choose among multiple platforms.
Each seller and buyer incurs linear transportation costs, τ_S and τ_B, respectively, that are proportional to the distance from his or her location to the location of the platform to which he or she will subscribe. If platform i attracts n_S^i and n_B^i users, an additional seller or buyer subscribing to platform i will obtain the following utility:

$$U_S^i = \beta_S + \alpha_S n_B^i - p_S^i - \textit{transportation cost}$$
$$U_B^i = \beta_B + \alpha_B n_S^i - p_B^i - \textit{transportation cost}$$

The surplus for a seller who subscribes to both platforms is simply the sum of the gross surpluses this seller could obtain on the two platforms, $U_S^{12} = 2\beta_S + \alpha_S(n_B^1 + n_B^2) - (p_S^1 + p_S^2)$, minus the total transportation cost incurred to subscribe to both platforms.
We consider a two-stage game. In the first stage, platforms simultaneously set their

[7] The Hotelling model with hinterlands has been studied by Armstrong and Wright (2009), Hagiu and Lee (2011), and Choi et al. (2018).

prices on each side of the market. In the second stage, users choose to whether subscribe to services offered by the platforms.
We compare different settings for the first stage according to whether platforms choose the sellers' price cooperatively. We search for the subgame perfect Nash equilibrium of this game. We solve the model by backward induction, starting from the last stage.

Users' subscription decisions **Sellers** can multihome (i.e., be active on both platforms).[8] Assuming that some multihome in equilibrium, as presented in Figure 1, they can be divided into three subintervals on the unit interval: sellers located on the left subscribe to platform 1 only, those located around the middle subscribe to both platforms, and those located on the right subscribe to platform 2 only. At the boundaries between these intervals, x_S^i, we find sellers who are indifferent between subscribing to platform i and not subscribing to this platform. Their respective locations are found as x_S^1 such that $u_S^1 = \tau_S x_S^1$, with $u_S^1 = \beta_S + \alpha_S n_B^1 - p_S^1$, and x_S^2 such that $u_S^2 = \tau_S(1 - x_S^2)$, with $u_S^2 = \beta_S + \alpha_S n_B^2 - p_S^2$. We assume for the present that $0 < x_S^2 < x_S^1 < 1$ (we provide necessary and sufficient conditions below), so that $n_S^1 = x_S^1$ and $n_S^2 = 1 - x_S^2$, with the multihoming sellers being located between x_S^2 and x_S^1.

The total number of sellers visiting platform i is thus given by:

$$n_S^i = \frac{\beta_S + \alpha_S n_B^i - p_S^i}{\tau_S} = \frac{u_S^i}{\tau_S}.$$

The number of sellers subscribing to platform i increases with the gross utility that sellers derive by subscribing to the platform and decreases with the transportation cost.

Buyers singlehome (i.e., they are active only on one platform). There are two types of buyers: contestable buyers, who are located in the unit interval, and captive buyers, who are located in the hinterlands. The location x_B of the buyer who is indifferent between the two platforms on the unit interval is given by $u_B^1 - \tau_B x_B = u_B^2 - \tau_b(1 - x_B)$, with $u_B^i = \beta_B + \alpha_B n_S^i - p_B^i$ and $i \in \{1, 2\}$. It follows that $n_B^1 = x_B$ and $n_B^2 = 1 - x_B$.

The location x_{Bc}^i of the captive buyer of platform i who is indifferent between subscribing to platform i and taking his or her outside option, which is normalised to 0, is given by $u_B^i - \tau_B x_{Bc}^i = 0$, which yields $n_{cB}^i = x_{Bc}^i$. The total number of buyers visiting platform i is thus given by:

$$n_B^i = \frac{1}{2} + \frac{u_B^i - u_B^j}{2\tau_B} + \lambda \frac{u_B^i}{\tau_B},$$

where $\lambda \geq 0$ is a parameter representing the relative importance of market expansion

[8] For the specification of the sellers' subscription functions, we follow Belleflamme and Peitz (2019).

possibilities. The number of buyers subscribing to platform i corresponds to half of the contestable buyers adjusted by a term representing the competition between platforms for these buyers and a term representing the number of captive buyers who join the platform. The parameter λ represents the market expansion possibilities. When $\lambda = 0$, we obtain the traditional competitive bottleneck model without demand expansion. We will refer to such a situation as a mature market where the possibility of gaining additional users is limited. By contrast, when $\lambda > 0$, we will refer to a market with demand expansion.

Figure 1 presents the demand on each side of the market, where the top line denotes the sellers, while the bottom line represents the buyers. Users on red lines subscribe to platform 1, while users on blue lines subscribe to platform 2.

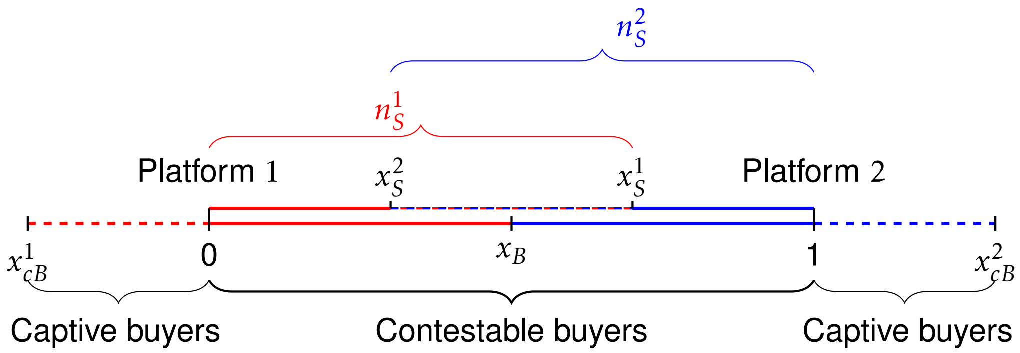

Figure 1: Demand configuration with multihoming on the seller side and singlehoming with hinterlands on the buyer side

By solving the system of four subscription equations, we obtain sellers' and buyers' subscriptions as a function of prices. Setting $\Delta \equiv \tau_S\tau_B - (1+\lambda)\alpha_S\alpha_B$, we can express the subscription demands as:

$$n_S^i = \frac{1}{\Delta + \alpha_B\alpha_S}\left[\frac{\alpha_S\tau_B}{2\Delta}\left[\Delta + \alpha_B\left[p_S^j - p_S^i\left(3 + \frac{2\Delta}{\alpha_S\alpha_B}\right)\right] + \tau_S\left[p_B^j - p_B^i\left(1 + \lambda\frac{2\Delta}{\tau_S\tau_B}\right)\right]\right] + \beta_S + \lambda\beta_B\alpha_S\right]$$

$$n_B^i = \frac{1}{\Delta + \alpha_B\alpha_S}\left[\frac{\tau_S\tau_B}{2\Delta}\left[\Delta + \alpha_B\left[p_S^j - p_S^i\left(1 + \lambda\frac{2\Delta}{\tau_S\tau_B}\right)\right] + \tau_S\left[p_B^j - p_B^i\left(1 + \lambda\frac{2\Delta}{\tau_B\tau_S}\right)\right]\right] + \lambda(\alpha_B\beta_S + \tau_S\beta_B)\right]$$

Lemma 4. *The sensitivity of sellers' subscriptions to platform i's price, i.e.,* $\frac{\partial n_S^i}{\partial p_S^i}$, *decreases with the demand expansion parameter,* λ. *In contrast, the sensitivity of sellers' subscriptions to platform* i *to the rival platform buyers' subscription price, i.e.,* $\frac{\partial n_S^i}{\partial p_B^j}$, *increases with the demand expansion parameter* λ.

Proof. See Appendix B. □

Now that we have obtained the users' subscription demands, we turn to the stage where platforms set subscription prices. We compare two scenarios, coopetition and competition, in two types of markets: mature markets (Section 3) and markets with demand expansion (Section 4). In the competition scenario, platforms compete on price on both sides, whereas in the coopetition scenario, they compete only on the buyer side and set prices jointly on the seller side.

4 Benchmark: coopetition in a mature market

In this section, we first set model assumptions and then analyse and compare the two different scenarios according to whether platforms can agree on sellers' subscription prices in mature markets.

4.1 Assumptions

In Appendix A, we present in detail the conditions that have to be met for the model equilibrium to be valid. First, there are conditions on the second-order conditions for the profit maximisation program and positive equilibrium profits. Second, we ensure partial multihoming on the seller side and full market coverage on contestable buyers' unit interval. We collect all these conditions for the competitive situation in Assumption 1 and for the coopetition situation in Assumption 2. All of them must hold to have a sharing equilibrium allowing us to compare the two environments.

Assumption 1 - (Belleflamme and Peitz, 2019) In the competitive bottleneck situation, parameters satisfy

$$8\tau_S\tau_B > (\alpha_S+\alpha_B)^2 + 4\alpha_S\alpha_B \tag{1}$$

$$\beta_S - c_S > \tau_S - \frac{1}{2}(\alpha_S+\alpha_B) \tag{2}$$

$$\beta_S - c_S < 2\tau_S - \frac{1}{2}(\alpha_S+\alpha_B) \tag{3}$$

$$\beta_B - c_B > \frac{1}{4\tau_S}\left(6(\alpha_S\alpha_B+\tau_S\tau_B) - 2(\beta_S-c_S)(\alpha_S+\alpha_B) - (\beta_B-\beta_S)^2\right) \tag{4}$$

Assumption 2 In the cooperative bottleneck situation, parameters satisfy

$$8\tau_S\tau_B > \left(\frac{\alpha_S\alpha_B}{\tau_S}\right)^2 + 4\alpha_S\alpha_B \tag{5}$$

$$\tau_S\tau_B > \alpha_S\alpha_B \tag{6}$$

$$4(\beta_S-c_S)^2 + 8\tau_S\tau_B > \alpha_S(8\alpha_S+\alpha_B) \tag{7}$$

$$\beta_S - c_S > \tau_S - \frac{\alpha_S}{2} \tag{8}$$

$$\beta_S - c_S < 2\tau_S - \frac{\alpha_S}{2} \tag{9}$$

$$\beta_B - c_B > \frac{1}{4\tau_S}\left(\alpha_B^2 + 3(2\tau_S\tau_B - \alpha_S\alpha_B) + (\alpha_S+\alpha_B)^2 - 2(\beta_S-c_S)(\alpha_S+\alpha_B)\right) \tag{10}$$

4.2 Pricing stage: competition versus coopetition

Competition on both sides

As a benchmark, we study the case in which platforms compete on both sides of the market.

Profit maximization Each platform i non-cooperatively sets its subscription prices p_S^i and p_B^i to maximise its profit:

$$\max_{\{p_S^i, p_B^i\}} \left\{ \left(p_S^i - c_S\right) n_S^i + \left(p_B^i - c_B\right) n_B^i \right\}$$

The best responses are defined by the first-order conditions and can be expressed (with the superscript CB standing for "competitive bottleneck") as:

$$p_S^{CB_i} = \frac{c_S}{2} + \frac{2\beta_S\left(\tau_S\tau_B - \alpha_S\alpha_B\right) + \tau_S\left(\alpha_B c_B - p_B^i\left(\alpha_S + \alpha_B\right)\right) + \alpha_S\left(\alpha_B p_S^j + \tau_S p_B^j + \tau_S\tau_B - \alpha_S\alpha_B\right)}{2\left(2\tau_S\tau_B - \alpha_S\alpha_B\right)}$$
$$p_B^{CB_i} = \frac{c_B}{2} + \frac{c_S\alpha_S - p_S^i\left(\alpha_S + \alpha_B\right) + \alpha_B p_S^j + p_B^j\tau_S + \tau_S\tau_B - \alpha_S\alpha_B}{2\tau_S}$$

We observe a negative relationship between platform i's own prices and a positive relationship with its rival's prices (i.e., strategically complementary).

Equilibrium prices When we solve the system of equations above, in symmetric equilibrium, the equilibrium prices are:

$$p_S^{CB*} = \frac{1}{2}\left(\beta_S + c_S + \frac{\alpha_S}{2} - \frac{\alpha_B}{2}\right)$$
$$p_B^{CB*} = c_B + \tau_B - \frac{\alpha_S}{4\tau_S}\left(2\beta_S - 2c_S + 3\alpha_B + \alpha_S\right)$$

The bottleneck situation implies that each platform has a monopoly over "access" to its single-homing buyers. Therefore, the subscription price charged by the platform to a seller is composed of half of the gross seller utility (i.e., without the transportation cost) generated by joining the platform, $1/2(\beta_S + 1/2\alpha_S)$.
This price component is decreased by the positive externality that this seller may have on buyers and increased by half of the cost incurred by the platform to serve a seller. The subscription price charged by the platform to a buyer corresponds to the cost to serve this buyer, which is increased by the market power gained by the differentiation between platforms and decreased by the benefit that an additional seller joins the platform (i.e., $\beta_S - c_S + 1/2\alpha_S$).

Coopetition

We now consider the scenario in which platforms engage in coopetition, that is, they set sellers' subscription prices cooperatively and buyers' prices non-cooperatively.

Profit maximization Platforms cooperatively set sellers' subscription prices to maximise their joint profit on that side:

$$\max_{\{p_S^i, p_S^j\}} \left\{ \left(p_S^i - c_S\right) n_S^i + \left(p_B^i - c_B\right) n_B^i + \left(p_S^j - c_S\right) n_S^j + \left(p_B^j - c_B\right) n_B^j \right\}$$

Simultaneously, each platform $i \in \{1,2\}$ independently sets its subscription price for buyers to maximise its own profit:

$$\max_{\{p_B^i\}} \left\{ \left(p_S^i - c_S\right) n_S^i + \left(p_B^i - c_B\right) n_B^i \right\}$$

Solving these maximisation programs leads to the following reaction functions (with the superscript "Coop" standing for "coopetition"):

$$p_S^{Coop_i} = \frac{(\beta_S + c_S)(\tau_B\tau_S - \alpha_B\alpha_S)}{2\tau_B\tau_S - \alpha_B\alpha_S} + \frac{\tau_S\left(\tau_B\alpha_S - (\alpha_B + \alpha_S)\left(p_B^i - p_B^j\right)\right) + \alpha_B\alpha_S\left(2p_S^j - \alpha_S\right)}{4\tau_B\tau_S - 2\alpha_B\alpha_S}$$

$$p_B^{Coop_i} = \frac{c_B + \tau_B + p_B^j}{2} + \frac{\alpha_S(c_S - \alpha_B) + \alpha_B p_S^j - (\alpha_S + \alpha_B) p_S^i}{2\tau_S}$$

As in the competitive bottleneck model, we observe a negative relationship between platform i's own prices and a positive relationship with its rival's prices.

Equilibrium prices When we solve the system of equations above, in symmetric equilibrium, the equilibrium prices (with the superscript "Coop" standing for "coopetition") are:

$$p_S^{Coop*} = \frac{1}{2}\left(\beta_S + c_S + \frac{1}{2}\alpha_S\right)$$

$$p_B^{Coop*} = c_B + \tau_B - \frac{\alpha_S}{2\tau_S}(\beta_S - c_S + \frac{1}{2}\alpha_S + 2\alpha_B)$$

Platforms charge a subscription price to sellers that corresponds to half of the willingness to pay of sellers (each seller has access to half of the buyers and, therefore, has a gross willingness to pay equal to $\frac{1}{2}\alpha_S$), which is increased by the stand-alone benefits from joining a platform, β_S and the marginal cost of that side, c_S. Note that this price is not adjusted for the cross-group effect that sellers exert on buyers. Platforms charge a subscription price to buyers equal to the Hotelling price, $c_B + \tau_B$, minus a term that depends on the size of the cross-group effects and on the parameters characterising the seller side ($c_S, \alpha_S,$ and τ_S).

Price comparison

We can now compare prices in the two scenarios, coopetition and competition.

Lemma 5. *In a mature market with positive network effects, sellers' (buyers') subscription prices are always higher (lower) in coopetition than in competition.*

Proof. The proof follows directly from the difference in the equilibrium prices in the two scenarios:

$$\Delta p_S = p_S^{Coop*} - p_S^{CB*} = \frac{1}{4}\alpha_B > 0$$
$$\Delta p_B = p_B^{Coop*} - p_B^{CB*} = -\frac{\alpha_S \alpha_B}{4\tau_S} = -\frac{\alpha_S}{\tau_S}\Delta p_S < 0$$

□

In the bottleneck model, if platforms cooperate on the multihoming side, a change in the sellers' subscription price leads to a change in the price on the competitive side as follows: $\Delta p_B = -\frac{\alpha_S}{\tau_B}\Delta p_S$, where $\Delta p_k = p_k^{Coop} - p_k^{CB}$ and $k \in \{S, B\}$. Platforms set a high price on the cooperative side and a low price on the other if and only if sellers enjoy the presence of buyers (i.e., $\alpha_S > 0$). Otherwise, both prices are above or below the static Nash levels. To limit the number of possible scenarios, we exclude in the remainder of this paper the scenario in which network externalities are non-positive.[9]

Coordination on the seller side leads platforms to set higher fees for sellers, even higher than the monopoly price. To see why, we compare the first-order condition of the platform's profit maximisation with respect to the seller subscription price in the two environments, which is given by $\frac{\partial \pi^i + \pi^j}{\partial p_S^i} = \frac{\partial \pi^i}{\partial p_S^i} + \frac{\partial \pi^j}{\partial p_S^i}$ under coopetition and $\frac{\partial \pi^i}{\partial p_S^i}$ under competition. Therefore, the difference in pricing incentives corresponds to the term $\frac{\partial \pi^j}{\partial p_S^i}$, which can be written as:

$$\frac{\partial \pi^j}{\partial p_S^i} = (p_S^j - c_S)\frac{\partial n_S^j}{\partial p_S^i} + (p_B^j - c_B)\frac{\partial n_B^j}{\partial p_S^i}$$

Using the subscription demands, we find that this term is equal to:

$$(p_S^j - c_S)\frac{\tau_B \alpha_S \alpha_B}{2\Delta(\Delta + \alpha_S \alpha_B)} + (p_B^j - c_B)\frac{\tau_S \tau_B \alpha_B}{2\Delta(\Delta + \alpha_S \alpha_B)}$$

Therefore, it is positive as long as the platform makes a positive margin on both sides (i.e., $p_B > c_B$ and $p_S > c_S$), and network effects are positive. The intuition is that under coopetition, platforms internalise that when they reduce their price on the seller side, this will harm the rival platform by making it less attractive to buyers, and through the indirect network effects, to sellers too. Therefore, coopetition leads the platforms to raise their subscription price for sellers compared to the case of full competition. However, as sellers become more valuable under coopetition and buyers exert a positive cross-group network effect on sellers, $\alpha_S > 0$, the competition for buyers is intensified, which leads to a lower price for buyers under coopetition than under competition.

[9]See Lefouili and Pinho (2020) for details on other scenarios.

4.3 Implications for profits and surplus

We now examine users' subscription levels and surplus, the platforms' profit, and total surplus under coopetition.

Users' subscriptions in equilibrium

Sellers The number of sellers subscribing to one of the platforms in the competitive and coopetitive symmetric equilibrium are:

$$n_S^{CB*} = \frac{1}{2\tau_S}\left(\beta_S - c_S + \frac{1}{2}(\alpha_B + \alpha_S)\right)$$
$$n_S^{Coop*} = \frac{1}{2\tau_S}\left(\beta_S - c_S + \frac{1}{2}\alpha_S\right)$$

Sellers' participation increases with the benefit from joining the platform, the magnitude of the network effects in the competitive case and with only the magnitude of the benefit that buyers exert on sellers in the coopetitive case. It decreases in both cases with platforms' differentiation for sellers and the stand-alone benefit and the marginal cost to serve a seller.

Lemma 6. *In a mature market with positive network effects, coopetition decreases the number of multihoming sellers.*

Proof. The proof follows directly from computing the difference between the two different environments:

$$n_S^{Coop*} - n_S^{CB*} = -\frac{\alpha_B}{4\tau_S} < 0$$

□

Buyers In competitive and coopetitive symmetric equilibria, the number of buyers subscribing to each platform is constant and shared equally between the two platforms in both environments:

$$n_B^{CB*} = n_B^{Coop*} = \frac{1}{2}$$

This result is explained by the participation constraints imposed in the model and the absence of expansion of buyers' demand in the mature market.

Participants' surplus

Sellers In the competitive and coopetitive symmetric equilibrium, by subscribing to a platform, a seller obtains a surplus (gross of transport costs) given by:

$$u_S^{CB*} = \frac{1}{2}\left(\beta_S - c_S + \frac{1}{2}(\alpha_S + \alpha_B)\right)$$
$$u_S^{Coop*} = \frac{1}{2}\left(\beta_S - c_S + \frac{1}{2}\alpha_S\right)$$

The utility of each seller decreases with coopetition. This is due to the price increase from coopetition.

The proof follows directly from computing the difference between the two different environments: $u_S^{Coop*} - u_S^{CB*} = \alpha_S \left(n_B^{Coop*} - n_B^{CB*}\right) - \left(p_S^{Coop*} - p_S^{CB*}\right) = -\frac{\alpha_B}{4} < 0$. There is no participation effect, as buyers are equally divided between the two platforms in both environments, and we have seen above that the price is higher in coopetition.

By taking into account the transportation cost, sellers' surplus is:

$$Surplus_S^* = \int_0^{n_S^*} (u_S^* - \tau_S x)dx + \int_{1-n_S^*}^{1} \left(u_S^* - \tau_S (1-x)\right) dx$$

Sellers located between 0 and n_S^*, with $* \in \{Coop*, CB*\}$, subscribe to platform 1, and sellers located between $1 - n_S^*$ and 1 subscribe to platform 2

Each earns a utility of u_S^* by joining a platform.

We obtain the following sellers' surplus:

$$Surplus_S^{CB*} = \frac{(2(\beta_S - c_S) + \alpha_S + \alpha_B)^2}{16\tau_S}$$
$$Surplus_S^{Coop*} = \frac{(2(\beta_S - c_S) + \alpha_S)^2}{16\tau_S}$$

Lemma 7. *In a mature market with positive network effects, sellers' surplus always decreases with coopetition. The difference between the two environments increases with network effects and decreases with the marginal cost.*

Proof. The proof follows from computing the difference between the two different environments:

$$Surplus_S^{Coop*} - Surplus_S^{CB*} = -\frac{\alpha_B (4(\beta_S - c_S) + \alpha_B + 2\alpha_S)}{16\tau_S}$$

Having $-\frac{\alpha_B(4(\beta_S - c_S) + \alpha_B + 2\alpha_S)}{16\tau_S} > 0$ implies that $4(\beta_S - c_S) < -\alpha_B - 2\alpha_S$. However, the competitive model participation constraint imposes that $\beta_S - c_S > \tau_S - \frac{1}{2}(\alpha_S + \alpha_B)$, so $-\frac{\alpha_B(4(\beta_S - c_S) + \alpha_B + 2\alpha_S)}{16\tau_S} < 0$. □

Buyers In the competitive and coopetitive symmetric equilibrium, by subscribing to a platform, a buyer obtains a surplus (gross of transport costs) given by:

$$u_B^{CB*} = \beta_B - c_B - \tau_B + \frac{(\alpha_B + \alpha_S)(2(\beta_S - c_S) + \alpha_B \alpha_S (\alpha_B + \alpha_S))}{4\tau_S}$$
$$u_B^{Coop*} = \beta_B - c_B - \tau_B + \frac{(\alpha_B + \alpha_S) 2(\beta_S - c_S) + \alpha_S (5\alpha_B + \alpha_S)}{4\tau_S}$$

Coopetition has ambiguous effects on the utility of each buyer with a positive price effect but a negative seller participation effect. Indeed, we have $u_B^{Coop*} - u_B^{CB*} = \alpha_B \left(n_S^{Coop*} - n_S^{CB*}\right) -$

$\left(p_B^{Coop*} - p_B^{CB*}\right)$. The participation effect is clearly negative for the utility of buyers, as coopetition reduces multihoming sellers on each platform, and the price effect is always positive for the utility of buyers because the buyer price is lower in coopetition. These two effects have opposite implications, and we need to examine how the effects of price and participation affect buyer surplus.

By taking into account the transportation cost, the surplus of buyers is:

$$Surplus_B^* = \int_0^1 u_B^* dx - 2\int_0^{\frac{1}{2}} \tau_B dx,$$

that is,

$$Surplus_B^{CB*} = \beta_B - c_B - \frac{5}{4}\tau_B + \frac{(\alpha_B + \alpha_S)\left(\beta_S - c_S + \frac{1}{2}(\alpha_B + \alpha_S)\right) + \alpha_B\alpha_S}{2\tau_S}$$

$$Surplus_B^{Coop*} = \beta_B - c_B - \frac{5}{4}\tau_B + \frac{(\alpha_B + \alpha_S)\left(\beta_S - c_S + \frac{\alpha_S}{2}\right) + 2\alpha_B\alpha_S}{2\tau_S}$$

Buyers' surplus increases with the stand-alone values and cross-group effects. It decreases with differentiation between platforms and marginal costs.

Lemma 8. *Coopetition has ambiguous effects on buyers' surplus. There are two possible outcomes:*

1. *If $\alpha_S > \alpha_B$, buyers are better off with coopetition (the price effect dominates)*
2. *If $\alpha_S < \alpha_B$, buyers are better off with competition (the participation effect dominates).*

Proof. The proof follows from computing the difference between the two different environments:

$$Surplus_B^{Coop*} - Surplus_B^{CB*} = \frac{1}{4\tau_S}(\alpha_S - \alpha_B)\alpha_B$$

□

If $\alpha_S > \alpha_B$, buyers are better off under coopetition. Buyers benefit from coopetition when the effect of price intensification is higher than the effect of mitigation. As we have seen previously, coordination on the seller side drives platforms to set higher fees for sellers. The magnitude of this price increase is higher with a higher α_B. However, as sellers become more valuable, competition for buyers intensifies. The magnitude of this competition intensification effect increases with α_S. Instead, if $\alpha_S < \alpha_B$, buyers are better off under full competition.

Platforms' profits

Finally, in competitive and coopetitive symmetric equilibria, platforms' profits are given by:

$$\pi^{CB*} = \frac{4(\beta_S - c_S)^2 + 8\tau_B\tau_S - \alpha_B^2 - 6\alpha_B\alpha_S - \alpha_S^2}{16\tau_S}$$
$$\pi^{Coop*} = \frac{4(\beta_S - c_S)^2 + 8\tau_B\tau_S - \alpha_S(8\alpha_B + \alpha_S)}{16\tau_S}$$

Platforms' profits increase with the difference between the stand-alone benefit and the cost of providing the service to sellers and with differentiation. It decreases with cross-group network effects.

Proposition 3. *Coopetition has ambiguous effects on platforms' profits. There are two possible outcomes:*

- *If $\alpha_B > 2\alpha_S$, platforms are better off in coopetition. The losses caused by the reduction in buyers' subscription price and the reduced number of multihoming sellers are more than compensated by the gains obtained from the increase in sellers' subscription price.*
- *If $\alpha_B < 2\alpha_S$, platforms are better off in competition. The losses caused by the reduction in buyers' subscription price and the reduced number of multihoming sellers are not compensated by the gains obtained from the increase in sellers' subscription price.*

Proof. The proof follows directly from computing the difference between the two different environments.

$$\pi^{Coop*} - \pi^{CB*} = \frac{\alpha_B(\alpha_B - 2\alpha_S)}{16\tau_S}$$

$\pi^{Coop*} > \pi^{CB*} \leftrightarrow \frac{\alpha_B(\alpha_B - 2\alpha_S)}{16\tau_S} > 0$, which is equivalent to $\alpha_B(\alpha_B - 2\alpha_S) > 0$. □

By cooperating, platforms can be worse off. This is the case when $\alpha_B > 2\alpha_S$, where the increase in profit on the seller side due to a higher seller fee is dominated by the decrease in profit on the buyer side due to a lower buyer fee.

Total surplus

We now aggregate buyers' and sellers' surplus with platforms' profits to make the total welfare comparison with $Total\ surplus^* = Surplus_S^* + Surplus_B^* + 2\pi^*$ with $* \in \{CB^*, Coop^*\}$. We obtain the following results:

$$Totalsurplus^{CB*} = \beta_B - c_B + \frac{3(2(\beta_S - c_S) + \alpha_B + \alpha_S)^2}{16\tau_S} - \frac{\tau_B}{4}$$
$$Totalsurplus^{Coop*} = \beta_B - c_B + \frac{(2(\beta_S - c_S) + 4\alpha_B + \alpha_S)(2(\beta_S - c_S) + 5\alpha_S)}{16\tau_S} - \frac{5\tau_B}{4}$$

Total surplus is increasing in the network effect intensity and in the difference between the stand-alone benefit and the cost of providing the service. Total surplus decreases in the degree of platform differentiation. We obtain the following results:

Proposition 4. *Coopetition always decreases total welfare in a mature market.*

Proof. The difference in total surplus between the coopetition and competition bottleneck models is given by:

$$Total\ surplus^{Coop*} - Total\ surplus^{CB*} = -\frac{\alpha_B}{4\tau_S}\left(\beta_S - c_S + \frac{\alpha_S}{2} + \frac{3\alpha_B}{4}\right)$$

Coopetition increases total welfare if and only if $4(\beta_S - c_S) + 2\alpha_S + 3\alpha_B < 0$. Integrating the sellers' participation constraints $\beta_S - c_S < 2\tau_S - \frac{\alpha_S}{2}$ with this previous expression, we obtain $4(2\tau_S - \frac{\alpha_S}{2}) + 2\alpha_S + 3\alpha_B < 0$. This would imply that $8\tau_S + 3\alpha_B < 0$, which is impossible with positive network effects. As a result, we have proven that coopetition always decreases total welfare in the context of positive network effects. □

In the context of a mature market, coopetition decreases total welfare. This may be because the low subscription price for buyers does not induce new buyers to join the platform, and thus, there are no additional benefits valued by sellers in the market (i.e., an increase in the number of buyers). In the next section, we allow for expansion of buyer demand.

5 Coopetition in a market with demand expansion

In this section, we compare the coopetition and competition scenarios in situations where platforms can expand their customer base on the buyer side. This occurs when the mass of captive users is nonzero, that is, $\lambda > 0$. As previously mentioned, some conditions have to be met for the competitive and coopetitive equilibrium to be valid; see Appendix C for details. The resolution of the model is similar to the mature market case. We solve the pricing stage of the game in coopetition and competition scenarios. We provide the prices, demands, users' surplus and platforms' profits in Appendix D.

The effect of coopetition on prices and multihoming sellers in a market with demand expansion is very similar to the effects described above for the scenario with a mature market. Platforms use cooperation on the multihoming side to increase sellers' subscription price. However, as sellers become more valuable, the competition for buyers is intensified, leading to a lower fee for buyers. In contrast to the case with a mature market, coopetition can now increase the number of buyers.

Proposition 5. *In a market with demand expansion and positive network effects, coopetition*

- *increases sellers' subscription price.*
- *decreases buyers' subscription price.*

- *decreases the number of multihoming sellers.*
- *has ambiguous effects on the number of buyers. There are two possible outcomes:*
  - *If $\alpha_S > \alpha_B$, the number of buyers increases with coopetition.*
  - *If $\alpha_S < \alpha_B$, the number of buyers decreases with coopetition.*

Proof. See Appendix E. □

There is no increase in sellers' multihoming in the context of the expansion of the buyer market. Numerical simulations show that platforms increase sellers' subscription prices faster than the expansion possibility on the buyer market (see Appendix E). However, now, the intensification of the competition on the buyer side under coopetition may lead to an increase in the number of buyers joining the market. When buyers benefit from weaker positive network externalities than sellers (if $\alpha_S > \alpha_B$), the price decrease leads new buyers to join the platform.

To complete this welfare analysis in a market with demand expansion, it remains to examine the impact of coopetition on users' welfare, platforms' profits and total welfare. In this context, the buyers' surplus corresponds to the sum of the surplus of contestable buyers, who are located on the unit interval, and of captive buyers, who are located in the hinterlands of the unit interval:

$$Surplus_B^* = \left[\int_0^1 (u_B^*)dx - 2\int_0^{\frac{1}{2}} \tau_B dx\right] + 2\lambda\left[\int_0^{n_{cB}^*} (u_B^* - \tau_B x)dx\right]$$

We cannot analytically compare surplus and profits. Thus, we have to resort to numerical simulations. We run several simulations that show that coopetition can increase total welfare. In such situations, sellers' surplus and platforms' profit seem to always be lower. In Figure 2, we provide a representative picture of these simulations for different values of β_S.[10]

Proposition 6. *In a market with demand expansion and positive network effects, coopetition can increase the number and surplus of buyers in a market with demand expansion. This may lead to an increase in the total welfare.*

Proof. See Figure 2 and Appendix E. □

Figure 2 presents representative results of coopetition leading to an increase in total surplus. For different values of the sellers' stand-alone benefit, we see the mechanism of the intensification of competition to attract buyers: sellers (buyers) pay higher (lower) subscription prices under coopetition. This leads to a decrease in the number of sellers and an increase in the number of buyers. We also observe that cooperation enhances buyers' surplus and decreases sellers' surplus and the platforms' profit. Finally, coopetition enhances total welfare. Even in this context, cooperation intensifies competition between platforms, and their profits

[10]For these figures, the parameters are $\beta_B = 4, \tau_S = 8, \tau_B = 1, c_S = 1, c_B = 1, \alpha_S = 2, \alpha_B = 1, \lambda = 1$. As the results show, all the constraints for the coopetition and competition models are respected.

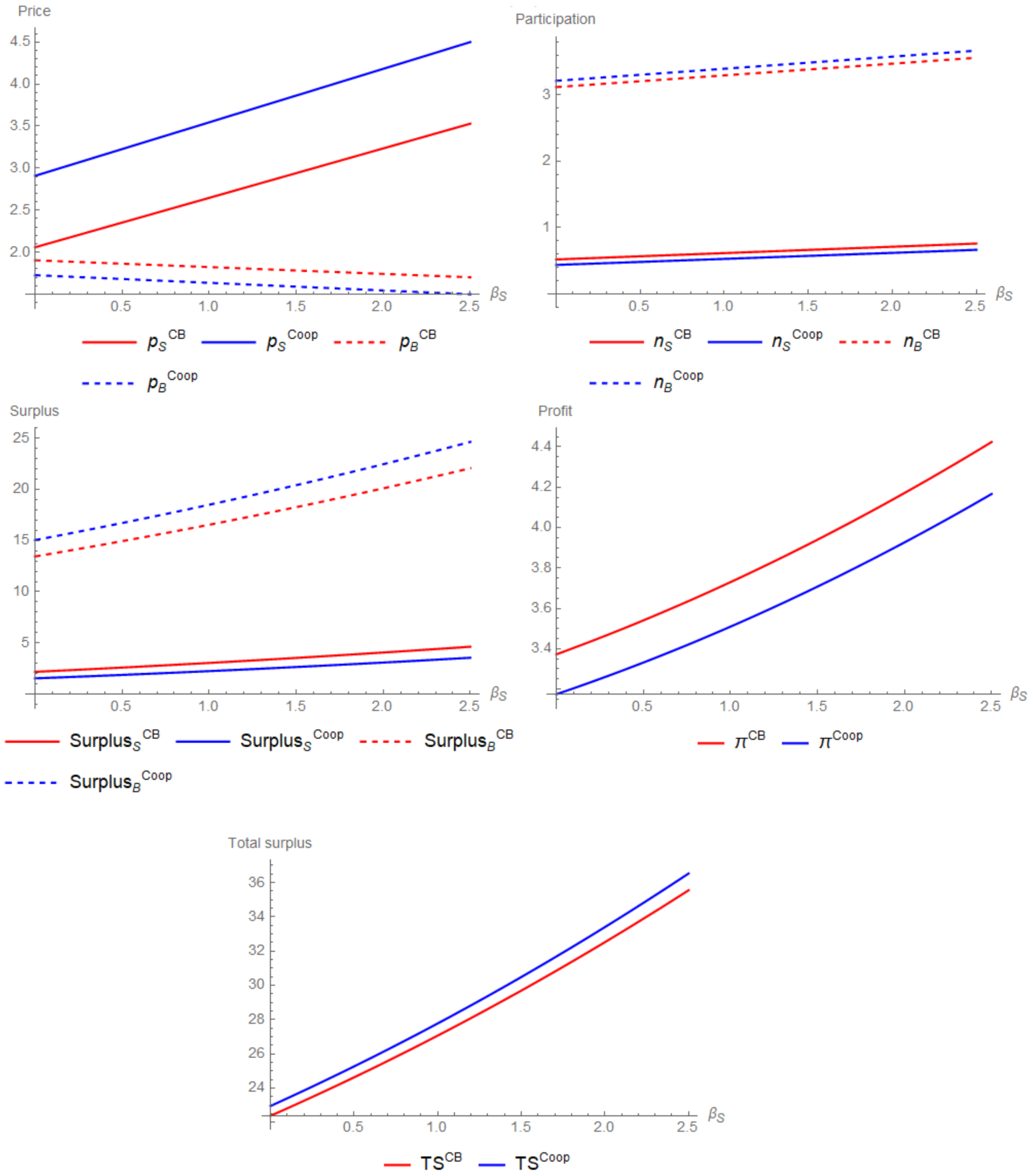

Figure 2: Representative numerical results of coopetition leading to an increase in total welfare for different values of β_S and for $\beta_B = 4, \tau_S = 8, \tau_B = 1, c_S = 1, c_B = 1, \alpha_S = 2, \alpha_B = 1, \lambda = 1$.

are still lower than in a situation of full competition. Increasing the sellers' stand-alone benefit reinforces these results.

6 Conclusion and policy implications

We have shown that allowing platforms to cooperate on sellers' subscription price does not imply that they will use this power to improve their common management of positive cross-group network effects. In contrast, platforms use it to increase sellers' subscription price, even above the monopoly price. However, as sellers become more valuable, the competition for buyers is intensified, leading to a lower fee for buyers. This mechanism seems to have been at play in the case of meal vouchers investigated by the French Competition Authority. Indeed, semi-collusion by the issuers of meal vouchers (i.e., the platforms) led to a price increase on the multihoming side and a price decrease on the singlehoming side.[11] This illustrates that allowing platforms to cooperate when they independently choose at least one other strategic variable can also increase effective competition among them (i.e., platforms' profits are lower in coopetition than in competition). In our model, this additional competition between platforms increases total surplus only if it leads new buyers to join platforms. This total surplus increase comes from the buyers' surplus that offsets the negative effects generated on sellers' surplus and platforms' profit. Even when cooperation between platforms improves total welfare, it outlines challenging questions on how to assess whether a fair proportion of the created value is passed on to users and the distribution between the different groups of users. Indeed, in our model, the interests of sellers and buyers are not aligned: buyers are better off with coopetition, while sellers are better off with competition.

[11] The effective commission rates decreased between 2010 and 2016 from 58% to 74% on the singlehoming emission side (i.e., annual averages of 13.3 % to 20.1%) and increased from a 23% to 64% rate on the multihoming acceptance side (i.e., annual averages of 3.5% to 8.5%). See https://www.autoritedelaconcurrence.fr/sites/default/files/integral_texts/2020-02/19d25.pdf

Appendix

2.A Coopetition in a mature market – Assumptions

A series of conditions have to be met for the competitive and coopetitive equilibria to be feasible.

First, the second order conditions of the profit maximisation program are $8\tau_S\tau_B > (\alpha_S + \alpha_B)^2 + 4\alpha_S\alpha_B$ in the competition environment (11) and $8\tau_S\tau_B > \left(\frac{\alpha_S\alpha_B}{\tau_S}\right)^2 + 4\alpha_S\alpha_B$ in the coopetition environment (15) and $\tau_S\tau_B > \alpha_S\alpha_B$ in both environments. These conditions requires that the perceived horizontal differentiation between the two platforms τ_S and τ_B should be sufficiently large with respect to the gains from trade α_S and α_B. In the competitive bottleneck environment, the condition (11) implies that even if platforms do not offer stand-alone utilities to sellers $\beta_S - c_S = 0$, equilibrium profits are strictly positive. In the coopetition model, we should add the following condition (17) that guarantee that equilibrium profits are strictly positive: $4(\beta_S - c_S)^2 + 8\tau_B\tau_S > \alpha_S(8\alpha_S + \alpha_B)$.

Second, we need to ensure that subscription to a platform should be sufficiently attractive. In particular, under both environment, there are partial multi-homing on sellers side and full market coverage on contestable buyers' unit interval. On the sellers' side, some (but not all) sellers should multihome in equilibrium. If some sellers multihome, this implies that all sellers participate, so $\frac{1}{2} < n_S^{CB*} < 1$ which implies that the sellers' margin, $\beta_S - c_S$, must be in the interval $\left[\tau_S - \frac{1}{2}(\alpha_S + \alpha_B), 2\tau_S - \frac{1}{2}(\alpha_S + \alpha_B)\right]$ in the competition environment and in the interval $\left[\tau_S - \frac{\alpha_S}{2}, 2\tau_S - \frac{\alpha_S}{2}\right]$ in the coopetition environment.

On the buyers' side, all buyers must be willing to participate; that is the indifferent buyer, located at $\frac{1}{2}$ must have a positive net surplus at equilibrium i.e., $\beta_B + \alpha_B n_S^* - p_B^* - \frac{1}{2}\tau_B > 0$ which implies that $\beta_B - c_B > \frac{1}{4\tau_S}\left[6(\alpha_S\alpha_B + \tau_S\tau_B) - 2(\beta_S - c_S)(\alpha_S + \alpha_B) - (\beta_B - \beta_S)^2\right]$ in the competition environment and $\beta_B - c_B > \frac{1}{4\tau_S}\left[3(2\tau_S\tau_B - \alpha_S\alpha_B) - 2(\beta_S - c_S)(\alpha_S + \alpha_B) + (\alpha_S + \alpha_B)^2 + \alpha_B^2\right]$ in the coopetition environment. In sum, all the previous assumptions must hold to have a sharing equilibrium allowing us to compare the two environments. We collect all these conditions for the competitive situation in Assumption 1 and for the coopetition situation in Assumption 2.

Assumption 1 - (Belleflamme and Peitz, 2019) In the competitive bottleneck situation, parameters satisfy

$$8\tau_S\tau_B > (\alpha_S + \alpha_B)^2 + 4\alpha_S\alpha_B \tag{11}$$

$$\beta_S - c_S > \tau_S - \frac{1}{2}(\alpha_S + \alpha_B) \tag{12}$$

$$\beta_S - c_S < 2\tau_S - \frac{1}{2}(\alpha_S + \alpha_B) \tag{13}$$

$$\beta_B - c_B > \frac{1}{4\tau_S}\left(6(\alpha_S\alpha_B + \tau_S\tau_B) - 2(\beta_S - c_S)(\alpha_S + \alpha_B) - (\beta_B - \beta_S)^2\right) \tag{14}$$

Assumption 2 In the cooperative bottleneck situation, parameters satisfy

$$8\tau_S\tau_B > \left(\frac{\alpha_S\alpha_B}{\tau_S}\right)^2 + 4\alpha_S\alpha_B \tag{15}$$

$$\tau_S\tau_B > \alpha_S\alpha_B \tag{16}$$

$$4(\beta_S - c_S)^2 + 8\tau_S\tau_B > \alpha_S(8\alpha_S + \alpha_B) \tag{17}$$

$$\beta_S - c_S > \tau_S - \frac{\alpha_S}{2} \tag{18}$$

$$\beta_S - c_S < 2\tau_S - \frac{\alpha_S}{2} \tag{19}$$

$$\beta_B - c_B > \frac{1}{4\tau_S}\left(\alpha_B^2 + 3(2\tau_S\tau_B - \alpha_S\alpha_B) + (\alpha_S + \alpha_B)^2 - 2(\beta_S - c_S)(\alpha_S + \alpha_B)\right) \tag{20}$$

2.B Proof of Lemma 1

In this proof, we show that the sensitivity of sellers' subscriptions to platform i's price, i.e., $\frac{\partial n_S^i}{\partial p_S^i}$, decreases with the demand expansion parameter, λ. In contrast, the sensitivity of sellers' subscriptions to platform i to the rival platform buyers' subscription price, i.e., $\frac{\partial n_S^i}{\partial p_B^j}$, increases with the demand expansion parameter λ.

Recalling the second order condition $\tau_B\tau_S - (1+\lambda)\alpha_B\alpha_S > 0$, the subscription demand sensibility to prices are:

$$\frac{\partial}{\partial \lambda}\left[\frac{\partial n_S^i}{\partial p_S^i}\right] = -\frac{1}{2}\alpha_B \alpha_S \tau_B \left(\frac{1}{((\lambda+1)\alpha_B\alpha_S - \tau_B\tau_S)^2} + \frac{1}{(\lambda\alpha_B\alpha_S - \tau_B\tau_S)^2}\right) < 0$$

$$\frac{\partial}{\partial \lambda}\left[\frac{\partial n_S^i}{\partial p_B^i}\right] = -\tau_B \alpha_S \tau_S \left(\frac{\alpha_B^2\alpha_S^2}{2(\lambda\alpha_B\alpha_S - \tau_B\tau_S)^2((\lambda+1)\alpha_B\alpha_S - \tau_B\tau_S)^2} + \frac{1}{(\tau_B\tau_S - \lambda\alpha_B\alpha_S)(\tau_B\tau_S - (\lambda+1)\alpha_B\alpha_S)}\right)$$

$$< 0$$

$$\frac{\partial}{\partial \lambda}\left[\frac{\partial n_S^i}{\partial p_S^j}\right] = \frac{1}{2}\alpha_B \tau_B \alpha_S \left(\frac{1}{((\lambda+1)\alpha_B\alpha_S - \tau_B\tau_S)^2} - \frac{1}{(\lambda\alpha_B\alpha_S - \tau_B\tau_S)^2}\right) < 0$$

$$\frac{\partial}{\partial \lambda}\left[\frac{\partial n_S^i}{\partial p_B^j}\right] = \frac{\alpha_S^2\alpha_B\tau_B\tau_S}{2(\tau_B\tau_S - \lambda\alpha_B\alpha_S)(\tau_B\tau_S - (\lambda+1)\alpha_B\alpha_S)}\left(\frac{1}{\tau_B\tau_S - (\lambda+1)\alpha_B\alpha_S} + \frac{1}{\tau_B\tau_S - \lambda\alpha_B\alpha_S}\right) > 0$$

2.C Coopetition with hinterlands – Assumptions

A series of conditions have to be met for the competitive and coopetitive equilibrium to be valid in markets with demand expansions environments. To compare the competitive and coopetition bottleneck models, we have to impose the most restrictive assumptions of each model.

First, in order to have concave profit functions, the second order conditions for the maximisation program are $4\tau_B\tau_S(\alpha_S\alpha_B + 2\Delta) > (\alpha_B + \alpha_S)^2(\tau_B\tau_S + 2\lambda\Delta)$ in the competition environment and $8\tau_B\tau_S\tau_S(\tau_B\tau_S + 2\lambda\Delta) > \alpha_B\alpha_S\left[8\lambda(1+\lambda)\tau_S(\alpha_S\alpha_B + 2\Delta) + \tau_B\left(\alpha_B\alpha_S + 4\tau_S^2\right)\right]$ in the coopetition environment and $\Delta > 0$ in both environments. As the mature markets assumptions, the perceived horizontal differentiation between the two platforms should be sufficiently large with respect to the gains from trade α_S and α_B in markets with demand expansion.

Second, subscription to a platform should be sufficiently attractive to drive all users to participate. Some (but not all) sellers should multihome at equilibrium. If some sellers multihome, this implies that all sellers participate, so $\frac{1}{2} < n_S^{CB*} < 1$ which implies that the difference between the sellers' stand-alone benefit and the platforms' cost to provide them the service should be between (21) and (22) in the competitive botteleneck model and (26) and (27) in the coopetitive bottleneck model. On the buyers' side, all buyers must be willing to participate; i.e., $\alpha_B n_S^{CB} - p_B^{CB} - \frac{1}{2}\tau_B > 0$ which implies that the difference between the buyers' stand-alone benefit and the platforms' cost to provide them the service should be less than (23) in the competitive botteleneck model and (28) in the coopetitive bottleneck model.

Assumption 3 . In the competitive bottleneck situation with demand expansion, parameters satisfy

$$\beta_S - c_S > \tau_S - \frac{(\alpha_S + \alpha_B)(\tau_S\tau_B + 2\Delta\lambda)(2\lambda(\beta_B - c_B + \alpha_S + \alpha_B) + \tau_B)}{2\tau_B(\lambda\alpha_S\alpha_B + \tau_S\tau_B + 4\Delta\lambda)} \tag{21}$$

$$\beta_S - c_S < 2\tau_S - \frac{(\alpha_S + \alpha_B)(\tau_S\tau_B + 2\Delta\lambda)(2\lambda(\beta_B - c_B + \alpha_S + \alpha_B) + \tau_B)}{2\tau_B(\lambda\alpha_S\alpha_B + \tau_S\tau_B + 4\Delta\lambda)} \tag{22}$$

$$\beta_B - c_B > \tau_B + \frac{\Delta\tau_B}{(2\tau_B)\tau_S + 4\Delta\lambda} - \frac{\alpha_B + \alpha_S}{4\tau_S}(2(\beta_S - c_S) + (\lambda+1)(\alpha_B + \alpha_S)) \tag{23}$$

$$4\tau_S\tau_B(\alpha_S\alpha_B + 2\Delta) > (\alpha_S + \alpha_B)^2(\tau_S\tau_B + 2\Delta\lambda) \tag{24}$$

$$\tau_S\tau_B > (1+\lambda)\alpha_S\alpha_B \tag{25}$$

Assumption 4 . In the coopetitive bottleneck situation, parameters satisfy

$$\beta_S - c_S > \tau_S - \frac{(2\Delta\lambda(\alpha_S + \alpha_B) + \alpha_S\tau_S\tau_B)(\lambda(2\beta_B - 2c_B + \alpha_S + \alpha_B) + \tau_B)}{2\tau_B(\tau_S\tau_B + 4\Delta\lambda)} \tag{26}$$

$$\beta_S - c_S < 2\tau_S - \frac{(2\Delta\lambda(\alpha_S + \alpha_B) + \alpha_S\tau_S\tau_B)(\lambda(2\beta_B - 2c_B + \alpha_S + \alpha_B) + \tau_B)}{2\tau_B(\tau_S\tau_B + 4\Delta\lambda)} \tag{27}$$

$$\beta_B - c_B > \tau_B - \frac{(\alpha_B + \alpha_S)(2(\beta_S - c_S) + (\lambda+1)(\alpha_B + \alpha_S))}{4\tau_S} + \frac{\tau_B\left((\lambda+1)\alpha_B^2 - \tau_B\tau_S + 3\Delta\right)}{4\tau_B\tau_S + 8\Delta\lambda} \tag{28}$$

$$8\tau_S\tau_B^2(\tau_S\tau_B + 2\Delta\lambda) > \alpha_S\alpha_B\left(8\lambda\tau_S(1+\lambda)(\alpha_S\alpha_B + 2\Delta) + \alpha_S\alpha_B\tau_B + 4\tau_B\tau_S^2\right) \tag{29}$$

$$\tau_S\tau_B > (1+\lambda)\alpha_S\alpha_B \tag{30}$$

2.D Coopetition with hinterlands – Expressions

In the following subsections, we present the prices, user participation and surplus in the coopetition and competitive models in a market with demand expansion. We exhibit the competition bottleneck model (CB) parameters with the common part that we find in the associated coopetition' parameters. These common parts are designated by the letters A, B and C.

2.D.1 Sellers' subscription price

$$\begin{aligned}
p_S^{CB*} = \\
&\frac{(\tau_B\tau_S + 2\Delta\lambda)(\tau_B\tau_S(4(\beta_S + c_S) + \alpha_S - \alpha_B) - 2\lambda(\tau_S(\beta_B - c_B)(\alpha_B - \alpha_S) + (\alpha_B + \alpha_S)(\beta_S\alpha_B + c_S\alpha_S)))}{4\tau_B\tau_S(\lambda\alpha_B\alpha_S + \tau_B\tau_S + 4\Delta\lambda) - 2\lambda(\alpha_B + \alpha_S)^2(\tau_B\tau_S + 2\Delta\lambda)} \\
&- \frac{2\tau_B(\beta_S + c_S)\tau_S(\tau_B\tau_S - \lambda\alpha_B\alpha_S)}{4\tau_B\tau_S(\lambda\alpha_B\alpha_S + \tau_B\tau_S + 4\Delta\lambda) - 2\lambda(\alpha_B + \alpha_S)^2(\tau_B\tau_S + 2\Delta\lambda)} \\
&= \frac{A}{B} \\
p_S^{Coop*} &= \frac{A + \alpha_B\tau_B\tau_S(2\lambda(\tau_S(\beta_B - c_B) + \beta_S\alpha_B - c_S\alpha_S) + \tau_B\tau_S)}{B + 2\lambda\alpha_B\tau_B\tau_S(\alpha_B - \alpha_S)}
\end{aligned}$$

2.D.2 Buyers' equilibrium price

$$\begin{aligned}
p_B^{CB*} &= \frac{2\tau_B(\tau_B\tau_S - \lambda\alpha_B\alpha_S + \Delta)(\lambda\alpha_B(\beta_S - c_S) + 2\lambda\beta_B\tau_S + \tau_B\tau_S)}{4\tau_B\tau_S(\lambda\alpha_B\alpha_S + \tau_B\tau_S + 4\Delta\lambda) - 2\lambda(\alpha_B + \alpha_S)^2(\tau_B\tau_S + 2\Delta\lambda)} \\
&\quad - \frac{(\tau_B\tau_S + 2\Delta\lambda)(2\lambda(\alpha_B + \alpha_S)(\beta_B\alpha_S + \alpha_B c_B) + \tau_B(\alpha_S(2\beta_S + \alpha_B - 2c_S + \alpha_S) - 4c_B\tau_S))}{4\tau_B\tau_S(\lambda\alpha_B\alpha_S + \tau_B\tau_S + 4\Delta\lambda) - 2\lambda(\alpha_B + \alpha_S)^2(\tau_B\tau_S + 2\Delta\lambda)} \\
&= \frac{A}{B} \\
p_B^{Coop*} &= \frac{A - \alpha_B\tau_B(\alpha_S\tau_B\tau_S - 2\lambda\alpha_B(c_B\tau_S + c_S\alpha_S))}{B + 2\lambda\tau_B\tau_S\alpha_B(\alpha_B - \alpha_S)}
\end{aligned}$$

2.D.3 Sellers' equilibrium participation

$$\begin{aligned}
n_S^{CB*} &= \frac{(\alpha_B + \alpha_S)(2\lambda(\beta_B - c_B) + \tau_B)(\tau_B\tau_S + 2\Delta\lambda) + 2\tau_B(\beta_S - c_S)(\lambda\alpha_B\alpha_S + \tau_B\tau_S + 4\Delta\lambda)}{4\tau_B\tau_S(\lambda\alpha_B\alpha_S + \tau_B\tau_S + 4\Delta\lambda) - 2\lambda(\alpha_B + \alpha_S)^2(\tau_B\tau_S + 2\Delta\lambda)} \\
&= \frac{A}{B} \\
n_S^{Coop*} &= \frac{A - \alpha_B\tau_B(2\lambda(\tau_S(\beta_B - c_B) + \alpha_S(\beta_S - c_S)) + \tau_B\tau_S)}{B + 2\lambda\alpha_B(\alpha_B - \alpha_S)\tau_B\tau_S}
\end{aligned}$$

2.D.4 Buyers' equilibrium participation

$$\begin{aligned}
n_B^{CB*} &= \frac{(\tau_B\tau_S + 2\Delta\lambda)(\lambda(\beta_S - c_S)(\alpha_B + \alpha_S) + 2\lambda\tau_S(\beta_B - c_B) + \tau_B\tau_S)}{2\tau_B\tau_S(\lambda\alpha_B\alpha_S + \tau_B\tau_S + 4\Delta\lambda) - \lambda(\alpha_B + \alpha_S)^2(\tau_B\tau_S + 2\Delta\lambda)} \\
&= \frac{A}{B} \\
n_B^{Coop*} &= \frac{A}{B + \lambda\tau_B\tau_S\alpha_B(\alpha_B - \alpha_S)}
\end{aligned}$$

2.D.5 Sellers' surplus

$$\begin{aligned}
S_S^{CB*} &= \frac{\tau_S}{4}\left[\frac{(\alpha_B + \alpha_S)(2\lambda(\beta_B - c_B) + \tau_B)(\tau_B\tau_S + 2\Delta\lambda) - 2\tau_B(\beta_S - c_S)(\lambda(4\lambda + 3)\alpha_B\alpha_S - (4\lambda + 1)\tau_B\tau_S)}{2\tau_B\tau_S(\lambda\alpha_B\alpha_S + \tau_B\tau_S + 4\Delta\lambda) - \lambda(\alpha_B + \alpha_S)^2(\tau_B\tau_S + 2\Delta\lambda)}\right]^2 \\
&= \frac{\tau_S}{4}\left[\frac{A}{B}\right]^2 \\
S_S^{Coop*} &= \frac{\tau_S}{4}\left[\frac{A - \alpha_B\tau_B(\tau_S(2\lambda\beta_B - 2\lambda c_B + \tau_B) + 2\lambda\alpha_S(\beta_S - c_S))}{B + \lambda\alpha_B(\alpha_B - \alpha_S)\tau_B\tau_S}\right]^2
\end{aligned}$$

2.D.6 Buyers' surplus

The surplus of buyers corresponds to the surplus of contestable buyers, who are located in the unit interval, and of captive buyers, who are located at the hinterlands of the unit interval:

$$
\begin{aligned}
Surplus_B^* &= \left[\int_0^1 (u_B^*)dx - 2\int_0^{\frac{1}{2}} \tau_B dx\right] + 2\lambda\left[\int_0^{n_{cB}^*} (u_B^* - \tau_B x)dx\right] \\
&= S_B^* + 2\lambda S_{B-cB}^*
\end{aligned}
$$

Surplus of contestable buyers

$$
\begin{aligned}
S_B^{CB*} &= \frac{\tau_B}{4}\left[\frac{2\left(\left(\tau_B\tau_S + 2\Delta\lambda\right)\left(\left(\alpha_B+\alpha_S\right)\left(2\left(\beta_S - c_S\right) + \alpha_B + \alpha_S\right) + 4\tau_S\left(\beta_B - c_B\right)\right) - 2\tau_B\tau_S\left(\alpha_B\alpha_S + 2\Delta\right)\right)}{2\tau_B\tau_S\left(\lambda\alpha_B\alpha_S + \tau_B\tau_S + 4\Delta\lambda\right) - \lambda\left(\alpha_B+\alpha_S\right)^2\left(\tau_B\tau_S + 2\Delta\lambda\right)} - 1\right] \\
&= \frac{\tau_B}{4}\left[\frac{A}{B} - 1\right] \\
S_B^{Coop*} &= \frac{\tau_B}{4}\left[\frac{A + 2\alpha_B\left(\alpha_S - \alpha_B\right)\tau_S\tau_B}{B + \lambda\alpha_B\left(\alpha_B - \alpha_S\right)\tau_S\tau_B} - 1\right]
\end{aligned}
$$

Surplus of captive buyers

$$
\begin{aligned}
&S_{B-cB}^{CB} = \\
&\quad \frac{\tau_B}{16}\frac{\left[\left(\tau_B\tau_S + 2\Delta\lambda\right)\Big(2\left(\beta_S - c_S\right)\left(\alpha_B+\alpha_S\right) + 4\tau_S\left(\beta_B - c_B - 2\tau_B\right) + \left(2\lambda+1\right)\left(\alpha_B+\alpha_S\right)^2\Big) + 2\alpha_B\tau_B\alpha_S\tau_S\right]}{\Big[2\tau_B\tau_S\left(\lambda\alpha_B\alpha_S + \tau_B\tau_S + 4\Delta\lambda\right) - \lambda\left(\alpha_B+\alpha_S\right)^2\left(\tau_B\tau_S + 2\Delta\lambda\right)\Big]^3} \\
&\qquad \Big[2\tau_B\tau_S\left(\alpha_B\alpha_S + 2\Delta\right) - \left(\tau_B\tau_S + 2\Delta\lambda\right)\Big(2\left(\beta_S - c_S\right)\left(\alpha_B+\alpha_S\right) + 4\tau_S\left(\beta_B - c_B\right) + \left(\alpha_B+\alpha_S\right)^2\Big)\Big]^2 \\
&\qquad = \frac{\tau_B}{16}\frac{[A]}{[C]^3}[B]^2 \\
&S_{B-cB}^{Coop} = \frac{\tau_B}{16}\frac{\left[A - (2\lambda+1)\alpha_B\tau_B\tau_S\left(\alpha_B - \alpha_S\right)\right]}{\left[C + \lambda\alpha_B\tau_B\tau_S\left(\alpha_B - \alpha_S\right)\right]^3}\left[B + \alpha_B\tau_B\tau_S\left(\alpha_B - \alpha_S\right)\right]^2
\end{aligned}
$$

2.E Coopetition with hinterlands – Results

In this section, we show analytically that the effect of coopetition on prices and multihoming sellers in a market with demand expansion is very similar to the effects described above for the scenario with a mature market. Platforms use cooperation on the multihoming side to increase sellers' subscription price. However, as sellers become more valuable, the competition for buyers is intensified, leading to a lower fee for buyers. In contrast to the case with a mature market, coopetition can now increase the number of buyers when $\alpha_S > \alpha_B$.

2.E.1 Preliminary proof

This preliminary proof shows that $2\tau_B\tau_S\left(\tau_B\tau_S + \lambda\alpha_B\alpha_S + 4\Delta\lambda\right) > \lambda\left(\alpha_B + \alpha_S\right)^2\left(\tau_B\tau_S + 2\Delta\lambda\right)$.

Proof. The second order condition of the competitive model with demand expansion imposes that
$2\tau_B\tau_S\left(2\lambda\alpha_S\alpha_B + 4\Delta\lambda\right) > \lambda\left(\alpha_B + \alpha_S\right)^2\left(\tau_B\tau_S + 2\Delta\lambda\right)$.
As $2\tau_B\tau_S\left(\tau_B\tau_S + \lambda\alpha_B\alpha_S + 4\Delta\lambda\right) > 2\tau_B\tau_S\left(2\lambda\alpha_S\alpha_B + 4\Delta\lambda\right)$ because $\tau_B\tau_S > \lambda\alpha_B\alpha_S$, then
$2\tau_B\tau_S\left(\tau_B\tau_S + \lambda\alpha_B\alpha_S + 4\Delta\lambda\right) > \lambda\left(\alpha_B + \alpha_S\right)^2\left(\tau_B\tau_S + 2\Delta\lambda\right)$. □

2.E.2 Differences between model parameters

We show in this subsection that the results obtain in the model with demand expansion with positive network effects and positive stand-alone benefit cost (i.e., $\beta_S - c_S > 0$ and $\beta_B - c_B > 0$) correspond to the mechanism of intensified price competition (i.e., sellers (buyers) pay higher (lower) subscription prices under coopetition). The number of sellers is always lower under coopetition and the number of buyers increases under coopetition if and only if $\alpha_S > \alpha_B$. Otherwise, it decreases.

Proof. Recalling the Preliminary proof above and $\tau_B\tau_S > (1+\lambda)\alpha_B\alpha_S$, then the proof follows directly from computing the difference between the two different environments.

$$\Delta p_S = p_S^{Coop*} - p_S^{CB*} = \frac{\alpha_B\tau_B(\tau_B\tau_S-\lambda\alpha_B\alpha_S)(\tau_B\tau_S+4\Delta\lambda)\tau_S(\lambda(\beta_S-c_S)(\alpha_B+\alpha_S)+2\lambda\tau_S(\beta_B-c_B)+\tau_B\tau_S)}{\left[2\tau_B\tau_S(\tau_B\tau_S+\lambda\alpha_B\alpha_S+4\Delta\lambda)-\lambda(\alpha_B+\alpha_S)^2(\tau_B\tau_S+2\Delta\lambda)\right]\left[\tau_B\tau_S(\lambda\alpha_B(\alpha_B+\alpha_S)+2\tau_B\tau_S+8\Delta\lambda)-\lambda(\alpha_B+\alpha_S)^2(\tau_B\tau_S+2\Delta\lambda)\right]} > 0$$

$$\Delta p_B = p_B^{Coop*} - p_B^{CB*} = -\frac{\alpha_B\tau_B(\tau_B\tau_S-\lambda\alpha_B\alpha_S)[2\Delta\lambda(\alpha_B+\alpha_S)+\tau_B\alpha_S\tau_S][\lambda(\beta_S-c_S)(\alpha_B+\alpha_S)+2\lambda\tau_S(\beta_B-c_B)+\tau_B\tau_S]}{\left[2\tau_B\tau_S(\lambda\alpha_B\alpha_S+\tau_B\tau_S+4\Delta\lambda)-\lambda(\alpha_B+\alpha_S)^2(\tau_B\tau_S+2\Delta\lambda)\right]\left[\tau_B\tau_S(\lambda\alpha_B(\alpha_B+\alpha_S)+2\tau_B\tau_S+8\Delta\lambda)-\lambda(\alpha_B+\alpha_S)^2(\tau_B\tau_S+2\Delta\lambda)\right]} < 0$$

$$\Delta n_S = n_S^{Coop*} - n_S^{CB*} = -\frac{\alpha_B\tau_B(\lambda(\beta_S-c_S)(\alpha_B+\alpha_S)+2\lambda\tau_S(\beta_B-c_B)+\tau_B\tau_S)(\tau_B\tau_S(\lambda\alpha_B\alpha_S+\tau_B\tau_S+4\Delta\lambda)-\lambda\alpha_S(\alpha_B+\alpha_S)(\tau_B\tau_S+2\Delta\lambda))}{[2\tau_B\tau_S(\lambda\alpha_B\alpha_S+\tau_B\tau_S+4\Delta\lambda)-\lambda(\alpha_B+\alpha_S)^2(\tau_B\tau_S+2\Delta\lambda)][\tau_B\tau_S(\lambda\alpha_B(\alpha_B+\alpha_S)+2\tau_B\tau_S+8\Delta\lambda)-\lambda(\alpha_B+\alpha_S)^2(\tau_B\tau_S+2\Delta\lambda)]} < 0$$

$$\Delta n_B = n_B^{Coop*} - n_B^{CB*} = \frac{\lambda\tau_B\tau_S(\alpha_S-\alpha_B)(\tau_B\tau_S+2\Delta\lambda)\alpha_B(\lambda(\beta_S-c_S)(\alpha_B+\alpha_S)+2\lambda\tau_S(\beta_B-c_B)+\tau_B\tau_S)}{[2\tau_B\tau_S(\lambda\alpha_B\alpha_S+\tau_B\tau_S+4\Delta\lambda)-\lambda(\alpha_B+\alpha_S)^2(\tau_B\tau_S+2\Delta\lambda)][\tau_B\tau_S(\lambda\alpha_B(\alpha_B+\alpha_S)+2\tau_B\tau_S+8\Delta\lambda)-\lambda(\alpha_B+\alpha_S)^2(\tau_B\tau_S+2\Delta\lambda)]}$$

We see that $\Delta n_B > 0$ when $\alpha_S > \alpha_B$ and $\Delta n_B < 0$ when $\alpha_S < \alpha_B$ □

2.E.3 Numerical simulations

Numerical simulations show that the platforms increase the sellers' subscription price faster than the possibility of expanding the buyer market. With parameters $\beta_S = 4, \beta_B = 4, \tau_S = 8, \tau_B = 1, c_S = 1, c_B = 1, \alpha_S = 2, \alpha_B = 1, \lambda = 1$, we obtain the following Figure 3[12]:

[12]We obtain the same result for all simulations that are presented below.

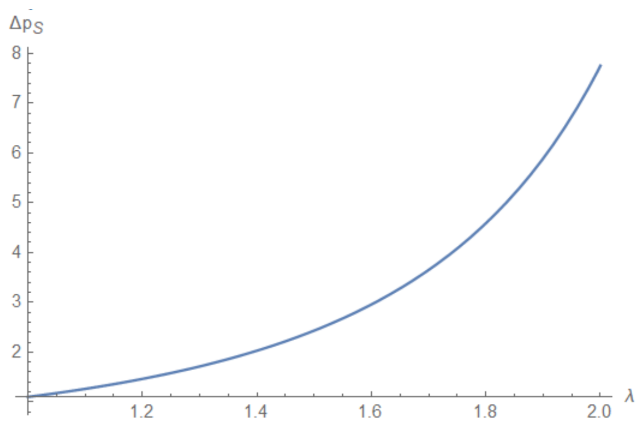

Figure 2.E.1: Sellers' subscription price increase with demand expansion

	Competitive Bottleneck	Coopetition	Δ(coop−CB)
Price sellers	2.6	3.5	0.90
Price Buyers	1.8	1.6	−0.19
Number of sellers	0.62	0.53	−0.087
Number of buyers	3.3	3.4	0.10
Sellers' Surplus	3.1	2.2	−0.80
Buyers' Surplus	17.	19.	2.0
Profit	3.7	3.5	−0.22
Total wefare	27.	28.	0.71

Figure 2.E.2: Parameter table for $\beta_B = 4, \beta_B = 4, \tau_S = 8, \tau_B = 1, c_S = 1, c_B = 1, \alpha_S = 2, \alpha_B = 1, \lambda = 1.$

In Figure 4, we see for specific parameters the intensification of competition mechanism to attract buyers: sellers (buyers) pay higher (lower) subscription prices with coopetition. This leads to a decrease in the number of sellers and an increase in the number of buyers. We also observe that this situation enhances buyers' surplus and decreases sellers' surplus and platforms' profit. Finally, coopetition enhances total welfare.

These key findings are obtained for numerous ranges of parameters. In particular for:

- $\beta_B = [1;4], \beta_B = 4, \tau_S = 8, \tau_B = 1, c_S = 1, c_B = 1, \alpha_S = 2, \alpha_B = 1, \lambda = 1$
- $\beta_B = 4, \beta_B = 4, \tau_S = [8;10], \tau_B = 1, c_S = 1, c_B = 1, \alpha_S = 2, \alpha_B = 1, \lambda = 1$
- $\beta_B = 4, \beta_B = 4, \tau_S = 8, \tau_B = 1, c_S = [23/6;49/12], c_B = 1, \alpha_S = 2, \alpha_B = 1, \lambda = 1$

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Chapter 3

Platform interoperability with multi-homing users and market dominance

"*The Internet was made in universities and it was designed to interoperate. And as we've commercialized it, we've added more of an island-like approach to it, which I think is a somewhat a shame for users.*" Larry Page, Google cofounder, December 11, 2012.[1]

1 Introduction

The Internet was originally conceived as an interoperable network between open systems.[2] For example, Email services are based on open and interoperable protocols for communicating online, regardless of a person's email service or the type of device they use to send email. In contrast, today's most widely used instant messaging services use proprietary protocols, and users cannot send messages from one messaging service to another (e.g., from WhatsApp to WeChat). This may lead users not to choose their preferred service but to adopt the service that offers the best compromise between its intrinsic value and the level of participation of other users.

In particular, users might be deterred to switch to a new entrant offering a better service if they have pessimistic expectations regarding the number of other users joining the entrant. Making a dominant strategy for users to migrate is the only way for the entrant to gain market share. That is, users should find it convenient to migrate regardless of what other users do. Therefore, entrants find it profitable to enter the market only if the quality gap is large enough.

This chapter is co-authored with Guillaume Thébaudin.

[1] Fortune, *Larry Page on Google*, December 11, 2012.

[2] Open Systems Interconnection (OSI), a comprehensive set of standards for computer networks, was developed to ensure interoperability within the communications system, regardless of technology type, vendor and model. However, too slowly formalised and too complex, it was overtaken by TCP-IP, which was widely adopted by businesses. Implementing homogenous networks based on proprietary architectures or interconnect heterogeneous systems with TCP-IP based products is easier and quicker. See IEEE spectrum, *OSI: the Internet that wasn't*, 30 July 2013.

This leads to static inefficiency since higher quality entrants may fail to conquer the market.[3]

In addition to this collective coordination problem, users may face individual switching costs. Switching costs arise when users generate content on their platforms (e.g., Youtube, Facebook or Deezer) but cannot migrate their data to a competing platform. For example, a user may upload photos and personal information to Facebook but may not easily download its data and move it to another social media. Instead, the user would have to start from scratch, re-upload their photos and their personal information on the new platform. An online seller with hundreds of product reviews and ratings on Amazon may face a similar challenge when migrating to a different platform. The right to data portability may be a way to reduce these switching costs. Such a right has been attributed in the EU to users over their data. The effect of data portability on entry is, however, ambiguous (Lam and Liu (2020)).

The possibility for users to multihome, that is, adopt and use two platforms, enables them to join their favoured platform while still benefiting from the network effects of the larger platform. However, multihoming can be costly, as users may incur high transportation costs to benefit from the network of their non-preferred platform and have to pay the price of both platforms.

Interoperability (or compatibility) is often cited as a possible regulatory instrument to stimulate entry and enhance the contestability of a dominant platform in such situations, and more generally in digital markets.[4] Interoperability refers to "the ability of two or more systems or components to exchange information and to use the information that has been exchanged".[5] Interoperability hence relates to shared standards across platforms.

Mandating interoperability between platforms would enable users present on one platform to interact with users of other platforms.

In this paper, we study the welfare implications of imposing different levels of interoperability between two horizontally differentiated platforms with differences in the size of their installed base. The large (or incumbent) platform has captive users acquired through its past presence on the market, and the small (or entrant) platform has not. Following Bakos and Halaburda (2020), we assume that users can multihome on both sides and do not derive additional value from interacting with the same person on two platforms. Interoperability enables users of one platform to interact directly with users of the other side present on the other platform. Different levels of interoperability can be interpreted as different levels of interconnection quality or the possibility to use all interaction functionalities (e.g., image or video transfer). Perfect interoperability allows users to benefit from global network effects without multihoming costs while using their preferred platform. With degraded interoperability, users have a degraded experience when interacting with users of the other platform, making some of them multihome.

[3] See Caillaud and Jullien (2003), Jullien et al. (2016) and Hałaburda and Yehezkel (2016). Halaburda and Yehezkel (2018) examine the competition between focal and non-focal platforms that differ in quality, and show that the ability of the high-quality but non-focal platform to win the market is affected by the initial degree of focality.

[4] OECD Competition Committee, Discussion Paper, *Data portability, interoperability and digital platform competition*, 2021.

[5] IEEE Standard Computing Dictionary, 1990.

Our model highlights that interoperability has two opposing effects on users' multihoming decision, and thus, on platforms' demand. On the one hand, interoperability makes users of the other platform increasingly accessible directly from their preferred platform, thus decreasing the incentives for multihoming. On the other hand, as interoperability affects users' multi-homing decisions, it impacts the exclusivity of each platform's user base, which is the driver of multi-homing decisions, and thus increases platforms' demand.

The strength of the latter effect weakens as the level of interoperability increases, as users are increasingly able to reach exclusive users of the other platform directly from their preferred platform. Given these two effects, interoperability in our asymmetric framework has a differential effect on the demand for the two platforms. We show that the large platform is always penalised by the introduction of interoperability. Interoperability reduces the competitive advantage of having the largest user base and the network effects generated by it. The effects of interoperability on the small platform are ambiguous. For a low level of interoperability, the benefit of increased exclusive demand from users who prefer that platform is higher than the cost of losing its user base exclusivity. For a higher level of interoperability, however, the negative effect takes precedence over the benefit.

This paper contributes to the policy debate on interoperability imposed to dominant platforms. From a regulatory perspective, the optimal level of interoperability depends on the objective. If it maximises user surplus, the regulator should set the maximum level of interoperability. Instead, if its objective is to maximise market entry, the regulator should choose an intermediate level of interoperability that maximises the profit of the small platform. Finally, if it maximises total welfare, the regulator must choose either zero or complete interoperability depending on parameter values.

The remainder of the paper is organised as follows. In Section 2, we review the literature. In Section 3, we describe the base model. In Section 4, we analyse users' subscription decisions. In Section 5, we derive the equilibrium and analyse the welfare implications of different levels of interoperability. We conclude and expose our plans for future research in Section 6.

2 Literature review

This paper relates to three streams of literature.

The first stream concerns the analysis of competition in two-sided markets (Rochet and Tirole (2003), Rochet and Tirole (2006), Armstrong (2006)). Following Bakos and Halaburda (2020), our model considers competition between two-sided platforms and the possibility for users to multihome on both sides of the market. We adopt their benchmark case assumption that participants meeting on both platforms benefit only once (no double counting). Other papers have investigated the competition between platforms with different network sizes (e.g., Gabszewicz and Wauthy (2014)). We contribute to this strand of literature by introducing interoperability and studying how it affects multi-homing decisions.

Second, our paper relates to the literature on compatibility and interoperability among various products or networks. The mix-and-match literature studies compatibility without network effects. This literature (e.g., Matutes and Regibeau (1988), Economides (1989) Chou and Shy (1990), Matutes and Regibeau (1992), Kim and Choi (2015)) considers that a consumer must purchase different elements of a system to use it and derive utility from it (e.g., hardware and software). These papers analyse the incentives of firms to make components of different systems compatible. They show that compatibility reduces the incentive of competing firms to set low prices for components because low prices increase the sales of a compatible rival. However, users may benefit more from compatibility, allowing them to assemble systems closer to their preferred configuration.

Our model is closer to the system competition literature that studies compatibility when network effects are present (e.g., Katz and Shapiro (1986), Economides and Flyer (1997) and Malueg and Schwartz (2006)).[6] The standard model is a two-stage game where firms make compatibility decisions in the first stage and then engage in price or quantity competition in the second stage. In these settings, both firms must agree for their products to be compatible. Two primary forces influence whether or not compatibility arises in equilibrium. First, compatibility enhances the value of firms' products by increasing network effects. As this draws more users into the market, firms have a mutual interest in making their products compatible. Second, when firms have different installed bases (e.g., Crémer et al. (2000), Malueg and Schwartz (2006); Farrell and Klemperer (2007); Chen et al. (2009)), the larger firm loses its competitive advantage with compatibility. In contrast, the smaller firm always prefers products to be compatible because it benefits from a larger demand and can catch up with the large firm.

Crémer et al. (2000) study the misalignment of incentives in terms of level of interoperability between two networks competing *à la Cournot*, which are asymmetric with respect to the size of their installed base, but are viewed as perfect substitutes absent any network size differences. Different from their approach, we model two-sided platforms differentiated *à la Hotelling* with the possibility for users to multihome on both sides. This enables us to study how users' multihoming decisions are affected by interoperability.

Doganoglu and Wright (2006) also analyse the interplay between compatibility and multihoming (interpreted as the purchase of two incompatible network goods). They find that compatibility reduces the incentives to multihome. We differentiate from this paper by allowing users to make their multihoming decision endogenously and in a context with two asymmetric two-sided platforms.[7]

Finally, the theoretical literature on interoperability in the context of two-sided markets is scarce. Casadesus-Masanell and Ruiz-Aliseda (2009) find that incompatibility gives rise to asymmetric equilibria with a dominant platform that earns more than under compatibility. They

[6] Some of this work is discussed in the review of Farrell and Klemperer (2007).

[7] Doganoglu and Wright (2006) discuss how their setting and findings can be extended to two-sided networks. However, they consider only symmetric two-sided networks where firms charge identical prices on both sides, and thus, do not address the potential cross-subsidisation between sides.

also find that incompatibility generates larger total welfare than compatibility when horizontal differences between platforms are small. Maruyama and Zennyo (2015) analyse the unilateral choices of application compatibility by platforms and the endogenous affiliation of two different groups (content providers and users). Adner et al. (2020) investigate two asymmetric competing platforms which provide users with different standalone utilities. In their paper, both platforms generate profits through hardware sales and royalties from third-party content providers. They find that platforms' incentives to establish one-way compatibility come from the difference in their profits foci, i.e., the difference in profits from hardware sales and royalties.

3 Model

Two platforms facilitate the interaction between two groups of users, sellers and buyers. The incumbent platform, Platform 1, has a mass δ of exogenous captive users on each side of the market. Captive users buy only from Platform 1 and never consider buying from the alternative platform (e.g., because of strong horizontal preferences). The entrant, Platform 2, does not have any installed base, as it just entered the market.

The two platforms are competing on each side for a mass one of contestable users. Each platform $k \in \{1, 2\}$ charges a subscription price p_i^k on side $i \in \{B, S\}$, and incurs zero marginal cost when serving additional users. We assume that Platform 1 can price discriminate between its captive users and the contestable users. Therefore, in the following analysis we focus on the contestable segment only.

Users derive a standalone benefit from joining a platform, denoted by β, and a network benefit from each interaction with every user of the other side present on this platform, denoted by α.

Users perceive platforms as horizontally differentiated *à la Hotelling*. They are uniformly distributed along the unit interval, with Platform 1 located on the left and Platform 2 on the right of the interval, as shown in Figure 1. Each user incurs a linear transportation cost, τ, proportional to the distance from his location to the location of the platform to which he subscribes.

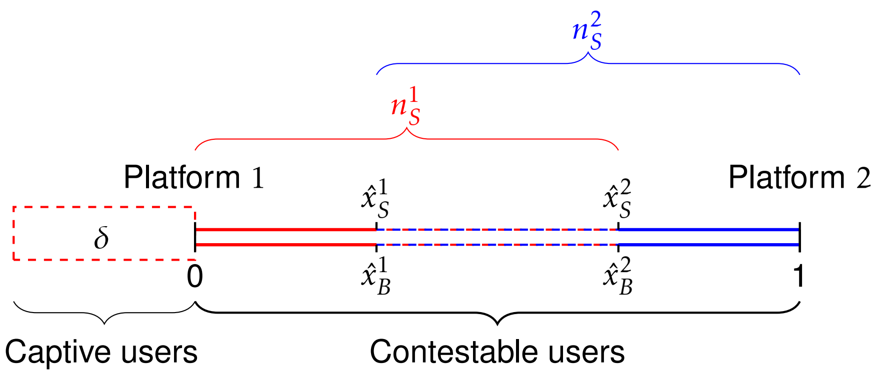

Figure 1: Demand configuration with multihoming on both sides.

Interoperability means that a user of a given platform can reach a user on the other side from the other platform with a quality of interaction $\theta \in [0,1]$, which represents the level of interoperability.[8] In our model, the level off interoperability is an exogenous parameter. In the absence of interoperability ($\theta = 0$), users cannot interact across platforms. With complete interoperability ($\theta = 1$), the quality of interaction is the same whether it takes place on the same platform or through interoperability. With partial interoperability ($\theta \in [0,1]$), finally, the quality of interaction through interoperability is lower than through the same platform. For instance, interoperability may allow to send a text message on the other platform but not to share one's location or a video.

Assuming that, on side j, Platform 1 attracts n_j^1 users in addition to its captive base δ and Platform 2 attracts n_j^2 users, a user on side i (with $i \neq j$) subscribing only to Platform 1 or Platform 2 (i.e., singlehoming) derives the following utility:

$$U_i^1 = \beta + \alpha(n_j^1 + \delta + \theta(1 - n_j^1)) - p_j^1 - \textit{transportation cost} \tag{1}$$

$$U_i^2 = \beta + \alpha(n_j^2 + \theta(1 - n_j^2 + \delta)) - p_j^2 - \textit{transportation cost} \tag{2}$$

where we use the fact that $n_j^2 = 1 - n_j^1$.

Interoperability allows a user to interact with users on the other side that he cannot reach on its platform. That is, a user of Platform 1 can reach $1 - n_j^1$ exclusive users of Platform 2 and a user of Platform 2 can reach $1 - n_j^2 + \delta$ exclusive users of Platform 1.

Users can also multihome (i.e., subscribe to both platforms). We assume that a multihoming user obtains a standalone benefit equal to $\beta(1+\rho)$ when joining both platforms, with $\rho \in \{0,1\}$. A multihomer reaches all users on the other side of the market. When multihoming occurs on both sides, a multihoming user of one group may meet certain users of the other group on both platforms, hence twice. Following Bakos and Halaburda (2020), we assume that users only benefit once from interacting with one particular user. That is, a multihomer who already met one particular user does not derive additional benefit from meeting the same user a second time on the other platform. So, a multihoming user of side i reaches all $(1+\delta)$ users of side j, and obtains the following utility:

$$U_i^M = (1+\rho)\beta + \alpha(1+\delta) - p_i^1 - p_i^2 - \tau. \tag{3}$$

We consider the following two stage game. In the first stage, the two platforms simultaneously set their prices for both sides of the market. In the second stage, users make their subscription decision. We look for the subgame perfect Nash equilibrium of this game.

We then study how the level of interoperability affects the equilibrium, and in particular, user behaviour and platforms' profits. Since we are interested in the relationship between interoperability and multihoming, we restrict our analysis to the equilibria with partial multihoming on both sides.

[8]This definition is an adaptation to two-sided markets of interoperability used in Crémer et al. (2000).

4 Users' demand

In this section, we study subscription decisions and how interoperability affects multihoming.

4.1 Users' subscription decisions

Users can singlehome or multihome. The incremental utility that a user located at x derives from joining Platform k in addition to Platform $-k$, denoted as $u(x;k|-k)$, is smaller than his utility to join only Platform k, $u(x;k)$. This is because the user can already interact on Platform $-k$ with users from the other group that he meets again on Platform k (which yields no additional utility due to our assumption of no double-counting). Thus, by joining a second platform, the user derives the utility of joining the two platforms less the utility he already obtains from his first-homing platform. Formally,

$$u(x;k|-k) = U^M - u(x;-k). \tag{4}$$

For example, consider a user on side i located at x, relatively closer to Platform 1, who first-homes on Platform 1. It then second-homes on Platform 2 if:

$$(1-x)\tau + p_i^2 \leq \rho\beta + \alpha(1-\theta)(1-n_j^1).$$

In words, the user subscribes to Platform 2 if the costs of doing so, composed of the transportation cost plus the fee charged by this platform (left-hand side), are lower than the benefits, composed of the incremental standalone benefit and the possibility to interact with this platform's exclusive users which is not enabled by interoperability (right-hand side). Holding prices and the number of exclusive users of the other platform constant, a higher level of interoperability therefore decreases the incentives to multihome. A similar reasoning applies for a user on side i located relatively closer to Platform 2.

Assuming that some users multihome in equilibrium, users on both sides can be divided into three sub-intervals of the unit interval, as shown in Figure 1. Users located on the left subscribe to Platform 1 only, those located around the middle subscribe to both platforms, and those located on the right subscribe to Platform 2 only. The boundaries are given by the marginal users $\hat{x}$ indifferent between joining Platform k in addition to Platform $-k$ and staying with Platform $-k$ only. Therefore, the marginal user derives no additional benefit by joining Platform k in addition to Platform $-k$, meaning that $u(\hat{x};k|-k) = 0$. Consequently, equation (4) can be rewritten as $U^M(\hat{x}) = u(\hat{x};-k)$ for the marginal user.

The location of the marginal user $\hat{x}_i^k$ indifferent between multihoming and homing only on

Platform k is then given by:

$$\hat{x}_i^1 = 1 - \frac{\rho\beta + \alpha(1-\theta)(1-n_j^1) - p_i^2}{\tau}, \tag{5}$$

$$\hat{x}_i^2 = \frac{\rho\beta + \alpha(1-\theta)(1-n_j^2+\delta) - p_i^1}{\tau}. \tag{6}$$

4.2 Demand

We suppose partial multihoming on both sides (i.e., $0 < \hat{x}_i^1 \leq \hat{x}_i^2 < 1$), so that $n_i^1 = \hat{x}_i^2$ and $n_i^2 = 1 - \hat{x}_i^1$, with the multihoming users being located between $\hat{x}_i^1$ and $\hat{x}_i^2$. We provide necessary and sufficient conditions for this to hold in equilibrium in Section 5.1.

Each platform has the same demand on both sides $i \in \{B, S\}$. With partial multihoming, we derive the following demand for each platform:

$$n_i^1 = \frac{\rho\beta + \alpha(1-\theta)(1-n_j^2+\delta) - p_i^1}{\tau}, \tag{7}$$

$$n_i^2 = \frac{\rho\beta + \alpha(1-\theta)(1-n_j^1) - p_i^2}{\tau}. \tag{8}$$

First, as found by Bakos and Halaburda (2020), with partial multihoming on both sides, the demand on one side of one platform depends on the price set by this platform for this side, as well as the demand on the other side for the other platform. There is thus no interaction in pricing between the different sides of one platform. This is because users only value interacting once with a user.

Second, absent interoperability ($\theta = 0$), the incumbency advantage (i.e., the presence of captive users on Platform 1) hurts the small platform in the following way. To access the δ captive users of Platform 1, users closer to Platform 2 have to second-home on Platform 1. Therefore, an increase in δ raises their incentives to multi-home, which renders them not exclusive to Platform 2. In turn, this exclusivity loss refrains contestable users closer to Platform 1 to join Platform 2, as they have access to these users directly on their prefered platform.

In what follows, we examine the extent to which platform interoperability can solve this demand distortion induced by the asymmetry in platform size.

4.3 Effect of interoperability on demand

Holding prices constant, the effect of interoperability on each platform's demand is given by:

$$\frac{\partial n_i^1}{\partial \theta} = -\frac{\alpha(1-n_j^2+\delta)}{\tau} - \frac{\alpha(1-\theta)}{\tau}\frac{\partial n_j^2}{\partial \theta}, \tag{9}$$

$$\frac{\partial n_j^2}{\partial \theta} = -\frac{\alpha(1-n_i^1)}{\tau} - \frac{\alpha(1-\theta)}{\tau}\frac{\partial n_i^1}{\partial \theta}. \tag{10}$$

From equation (9) and (10), we observe that interoperability has two effects on a platform's demand.

The first term in both equations represents the "multi-homing reducing" effect of interoperability. A higher level of interoperability allows users to better interact with the other platform's exclusive users from their preferred platform. Therefore, their incentive to multi-home decreases, reducing each platform's demand.

The second term in the equations represents the "user-base exclusivity shift" effect of interoperability. As interoperability affects users' multi-homing decisions, it impacts the exclusivity of each platform's user base, which is the driver of multi-homing decisions. This effect has the opposite sign of the variations of the other platform's demand with respect to interoperability. For example, if $\partial n_j^2/\partial\theta \geq 0$, that is, more users closer to Platform 1 decide to multi-home, then they become not exclusive to this platform anymore, which disincentivises users closer to Platform 2 to multi-home to access them as they are now accessible on their preferred platform. The strength of this effect decreases with θ. Indeed, the importance of the exclusivity of each platform user base in multi-homing decision is decreasing in the level of interoperability as users become increasingly reachable from their preferred platform through interoperability.

The asymmetry between the platforms regarding the presence of exclusive captive users leads to different balancing effects across platforms.

From equations (9) and (10), we see that the "multi-homing reducing" effect has a stronger negative impact on demand for Platform 1 than for Platform 2, due to the presence of captive users on the larger platform. Thus, for relatively low levels of interoperability, Platform 2 increases its number of exclusive users at a higher rate than Platform 1, and the higher is δ, the higher this effect. It is then likely that some users closer to Platform 1, who were not incentivised to second-home on Platform 2, now do so to continue having access to these users that become exclusive to Platform 2, meaning that the "user-base exclusivity shift" effect for this platform is positive. Therefore, for low levels of interoperability θ and a large enough number of captive users δ, we can have $\partial n_i^1/\partial\theta < 0$ and $\partial n_j^2 \partial\theta > 0$. For higher levels of interoperability, however, these users become increasingly reachable directly by first-homing, so that the demand of both firms is likely to decrease.

Solving the system of four subscription equations, given by (7) and (8), we obtain users' demands as a function of prices:

$$\begin{aligned} n_i^1 =& \frac{\tau\rho\beta + \alpha(1-\theta)\left(\tau(1+\delta) - \rho\beta - \alpha(1-\theta) + p_j^2\right) - \tau p_i^1}{\tau^2 - (\alpha(1-\theta))^2}, \\ n_i^2 =& \frac{\tau\rho\beta + \alpha(1-\theta)(\tau - \rho\beta - \alpha(1-\theta)(1+\delta) + p_j^1) - \tau p_i^2}{\tau^2 - (\alpha(1-\theta))^2}. \end{aligned} \tag{11}$$

Now that we have obtained the users' demands, we turn to the first stage of the game where platforms set subscription prices.

5 Equilibrium

In this section, we first define the model's assumptions and derive the equilibrium with partial multihoming on both sides of the market. Then, we analyse the effect of different levels of interoperability on platform profits and user surplus.

5.1 Model assumptions

In Appendix 3.A, we detail the conditions that have to be met for the model equilibrium to be valid. First, the second-order conditions for profit maximisation should hold and equilibrium profits be positive. These conditions require that $\tau > \alpha$.

Second, we assume partial multihoming on both sides at the equilibrium. That is, we must have $0 < \hat{x}_i^{1*} \leq \hat{x}_i^{2*} < 1$ for $i \in \{S, B\}$. Appendix 3.A.2 details how conditions translate in terms of the model parameters.

5.2 Profit maximisation

Platform 1 can price discriminate between its contestable and captive users. Therefore, we focus on pricing decisions for the contestable segment.

Each platform $k \in \{1, 2\}$ sets its prices to maximise its profit,

$$\max_{p_S^k, p_B^k} \left\{ p_S^k n_S^k + p_B^k n_B^k \right\}.$$

Solving for the first-order conditions, we obtain the best responses:

$$p_i^1 = \frac{1}{2\tau}[\tau\rho\beta + \alpha(1-\theta)(\tau(1+\delta) - \rho\beta - \alpha(1-\theta) + p_j^2)], \tag{12}$$

$$p_i^2 = \frac{1}{2\tau}[\tau\rho\beta + \alpha(1-\theta)(\tau - \rho\beta - \alpha(1-\theta)(1+\delta) + p_j^1)]. \tag{13}$$

First, as found by Bakos and Halaburda (2020), we observe no interdependence of prices on the two sides of the same platform.

Second, we observe that the strategic dependency of the price set by one platform for one side with the price set by the other platform for the other side decreases with the level of interoperability. In other words, there is a positive relationship between the best-response of platform k on side i with its rival's price on side j (i.e., strategic complementary). This is because if Platform k increases its price for side i, this reduces its demand on that side. The other Platform $-k$ has then additional exclusive users on side i, which, in turn, increases its demand for side j on that platform. This allows it to set higher prices. This effect is at play if users multihome. It disappears when users only single-home and access the other platform users only through interoperability.

The variation of the best responses with respect to the level of interoperability is given by:

$$
\begin{aligned}
\frac{\partial p_S^1}{\partial \theta} &= -\frac{\alpha}{2\tau}(\tau(1+\delta)-\rho\beta-\alpha(1-\theta)+p_B^2)+\frac{\alpha^2}{2\tau}(1-\theta)+\frac{\alpha}{2\tau}(1-\theta)\frac{\partial p_B^2}{\partial \theta} \\
\frac{\partial p_B^2}{\partial \theta} &= -\frac{\alpha}{2\tau}(\tau-\rho\beta-\alpha(1-\theta)(1+\delta)+p_S^1)+\frac{\alpha^2}{2\tau}(1-\theta)(1+\delta)+\frac{\alpha}{2\tau}(1-\theta)\frac{\partial p_S^1}{\partial \theta}
\end{aligned}
\tag{14}
$$

The first term in both equations represents the direct effect of interoperability, which decreases multihoming and demand. The second term represents the indirect effect of interoperability, which increases demand thanks to the increase in exclusive users. Finally, the last term represents the effect on the platform's price of a change in the other platform's price following a marginal increase in interoperability (competition effect).

5.3 Equilibrium prices

Solving for the system of equations given by (12) and (13), we obtain the equilibrium prices on side $i \in \{B, S\}$:

$$
\begin{aligned}
p_i^{1*} &= \frac{2\tau^2\rho\beta+\alpha(1-\theta)\Big((2\tau^2-(\alpha(1-\theta))^2)(1+\delta)-(\tau+\alpha(1-\theta))\rho\beta-\alpha\tau(1-\theta)\Big)}{4\tau^2-(\alpha(1-\theta))^2}, \\
p_i^{2*} &= \frac{2\tau^2\rho\beta+\alpha(1-\theta)\Big(2\tau^2-\tau\alpha(1-\theta)(1+\delta)-(\tau+\alpha(1-\theta))\rho\beta-(\alpha(1-\theta))^2\Big)}{4\tau^2-(\alpha(1-\theta))^2}.
\end{aligned}
\tag{15}
$$

Proposition 7. *The price set by the large platform is always (weakly) higher than the price set by the small platform. These prices are equal if and only if interoperability is perfect (i.e., $\theta = 1$). If the number of captive users is high enough, an increase in the level of interoperability leads the large platform to lower its price and the small platform to increase its price.*

Proof. The first part of the proposition follows directly by computing the difference in prices between the two different platforms:

$$
p_i^{2*} - p_i^{1*} = -\alpha\delta(1-\theta)\frac{\tau+\alpha(1-\theta)}{2\tau+\alpha(1-\theta)} \le 0. \tag{16}
$$

See Appendix 3.B.1 for the proof of the second part of the proposition. □

In equilibrium, each platform sets a subscription prices that takes into account the utility that it can generate exclusively for a user. Platform 1 benefits from a competitive advantage due to its captive users that it can leverage unless full interoperability is achieved. For relatively low levels of interoperability, Platform 2 can raise its prices through increases in its exclusive users, which in turn encourages other users close to the platform to join.

5.4 Users' subscriptions in equilibrium

In equilibrium, the platform's demand from users of side $i \in \{B, S\}$ are given by:

$$\begin{aligned} n_i^{1*} =& \frac{\Big(\rho\beta\tau + \alpha(1-\theta)\tau\Big)\Big(2\tau + \alpha(1-\theta)\Big)\Big(\tau - \alpha(1-\theta)\Big) + \delta\alpha(1-\theta)\tau\Big(2\tau^2 - (\alpha(1-\theta))^2\Big)}{\Big(\tau^2 - (\alpha(1-\theta))^2\Big)\Big(4\tau^2 - (\alpha(1-\theta))^2\Big)}, \\ n_i^{2*} =& \frac{\Big(\rho\beta\tau + \alpha(1-\theta)\tau\Big)\Big(2\tau + \alpha(1-\theta)\Big)\Big(\tau - \alpha(1-\theta)\Big) - \delta\Big(\alpha(1-\theta)\tau\Big)^2}{\Big(\tau^2 - (\alpha(1-\theta))^2\Big)\Big(4\tau^2 - (\alpha(1-\theta))^2\Big)}. \end{aligned} \tag{17}$$

Proposition 8. *The number of contestable users is always (weakly) higher on the large platform than on the small platform. The number of contestable users is the same in the absence of captive users (i.e., $\delta = 0$) or if there is perfect interoperability (i.e., $\theta = 1$).*

Proof. Recall that $\tau > \alpha$. The first part of the proposition then follows directly by computing the difference in number of users between the two platforms:

$$n^{2*} - n^{1*} = -(1-\theta)\frac{\alpha\tau\delta}{(2\tau + \alpha(1-\theta))(\tau - \alpha(1-\theta))} \leq 0. \tag{18}$$

When $\theta = 1$, $n^{1*} = n^{2*} = \frac{\beta\rho}{2\tau}$ and when $\delta = 0$, $n^{1*} = n^{2*} = \frac{\tau(\beta\rho+\alpha(1-\theta))}{(\tau+\alpha(1-\theta))(2\tau-\alpha(1-\theta))}$. □

5.5 Platforms' equilibrium profits

Finally, in equilibrium platforms' profits are given by:

$$\begin{aligned} \pi^1 =& 2\tau\frac{\Big((2\tau + \alpha(1-\theta))(\tau - \alpha(1-\theta))(\beta\rho + \alpha(1-\theta)) + \alpha\delta(1-\theta)\Big(2\tau^2 - \alpha^2(1-\theta)^2\Big)\Big)^2}{(2\tau + \alpha(1-\theta))^2(2\tau - \alpha(1-\theta))^2(\tau + \alpha(1-\theta))(\tau - \alpha(1-\theta))}, \\ \pi^2 =& 2\tau\frac{\Big((2\tau + \alpha(1-\theta))(\tau - \alpha(1-\theta))(\beta\rho + \alpha(1-\theta)) - \alpha^2\delta(1-\theta)^2\tau\Big)^2}{(2\tau + \alpha(1-\theta))^2(2\tau - \alpha(1-\theta))^2(\tau + \alpha(1-\theta))(\tau - \alpha(1-\theta))}. \end{aligned}$$

Proposition 9. *The profit of the large platform is always (weakly) higher than the profit of the small platform. The difference in profits decreases with the level of interoperability and increases with the number of captive users. Platforms obtain the same profit when there is perfect interoperability (i.e., $\theta = 1$) or no captive users (i.e., $\delta = 0$).*

Proof. The first part of the proposition follows directly by computing the difference in profits between the two platforms:

$$\pi^1 - \pi^2 = 2\alpha\delta(1-\theta)\tau\frac{2\beta\rho + \alpha(2+\delta)(1-\theta)}{4\tau^2 - \alpha^2(1-\theta)^2}. \tag{19}$$

If $\theta = 0$, the difference is equal to $2\alpha\tau\delta\frac{2\beta\rho+\alpha(2+\delta)}{(2\tau-\alpha)(2\tau+\alpha)}$, which is always positive. The same is true if $\delta = 0$. □

5.6 User surplus

Finally, we compute user surplus. A user obtains the following surplus (gross of transportation costs), depending on whether it joins Platform 1, Platform 2, or both platforms:

$$
\begin{aligned}
u_i^{1*} &= \beta + \alpha(n_j^{1*} + \delta) - p_i^{1*} \\
u_i^{2*} &= \beta + \alpha(n_j^{2*} + \theta(1 - n_j^{2*} + \delta)) - p_i^{2*} \\
u_i^{M*} &= (1+\rho)\beta + \alpha(1+\delta) - p_i^{1*} - p_i^{2*}
\end{aligned} \tag{20}
$$

Taking into account the transportation costs, user surplus is then:

$$
Surplus_i^* = \int_0^{1-n_i^{2*}} (u_i^{1*} - \tau x)dx + \int_{1-n_i^{2*}}^{n_i^{1*}} \left(u_i^{M*} - \tau\right)dx + \int_{n_i^{1*}}^{1} \left(u_i^{2*} - \tau(1-x)\right)dx
$$

Users located between 0 and $1 - n_i^{2*}$ subscribe only to Platform 1, users located between n_i^{1*} and 1 subscribe only to Platform 2 and those located between $1 - n_i^{2*}$ and n_i^{1*} multihome.

The expressions for user surplus are provided in Appendix 3.B.4. However, we could not analytically determine how user surplus and, consequently, total surplus are affected by different levels of interoperability. Thus, we have to resort to numerical simulations.

5.7 Effect of interoperability on user surplus and total surplus

We ran several simulations to study how interoperability affects user surplus and total surplus. In the following, we provide a representative picture of these simulations for different values of θ, starting from the users' subscription demand.[9]

First, we observe in Figures 2 and 3 that the demand n_i^{1*} and the price p_i^{1*} of Platform 1 are decreasing in the level of interoperability θ. Recall that absent interoperability, Platform 1 benefits from its δ captive users, as users first-homing on Platform 2 are highly incentivised to second-home on Platform 1, which increases the demand for this platform. An increase in interoperability decreases this incentive to multihome as captive users become increasingly reachable directly from Platform 2. Facing such a decrease in attractivity, Platform 1 decreases its price on both sides. It follows that its profit is always decreasing in θ, as can be seen in Figure 4.

Regarding Platform 2, we observe that n_i^{2*} is slightly decreasing for θ lower than 0.2, after which it starts to decrease more rapidly, albeit at a slower rate than the demand of Platform 1.

The price p_i^{2*} is concave, increasing for θ lower than 0.55 and decreasing for higher levels of interoperability. Interoperability benefits a singlehomer on a small platform more than a user on a large platform, because interoperability gives them access to a larger network. Interoperability allows a user who prefers Platform 2, but who also needed to join Platform 1 to benefit from its

[9]For these figures, the parameters are set to $\beta = 6$, $\alpha = 2$, $\gamma = 1.5$, $\tau = 6$ and $\rho = 1$. As the results show, all the constraints are respected.

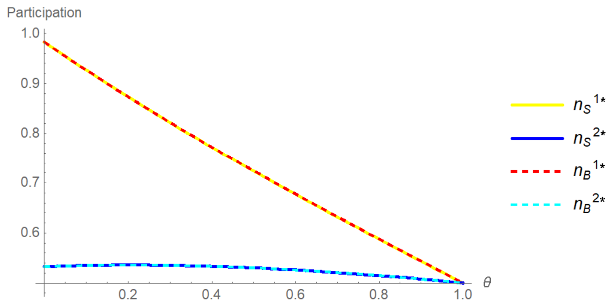

Figure 2: Users' subscription demand

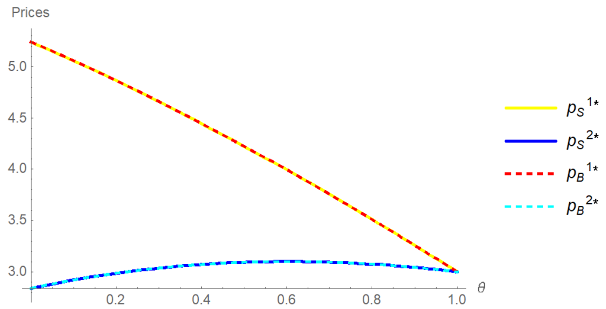

Figure 3: Platforms' subscription prices

essential network effects to stop multihoming and stay only on Platform 2. This user becomes exclusive to Platform 2, which makes this platform more attractive to other users. For low levels of interoperability, this effect is dominant for Platform 1 and thus increases its attractiveness, which it can exploit by raising its price.

However, for higher levels of interoperability, the negative effect on the platform's attractiveness of the loss of user base exclusivity due to interoperability becomes greater than the first effect of additional exclusive users due to interoperability for Platform 2. The small platform lowers its price to cope with its loss of attractiveness.

As such, we observe in Figure 4 and 5 that the profit of Platform 2 is concave.

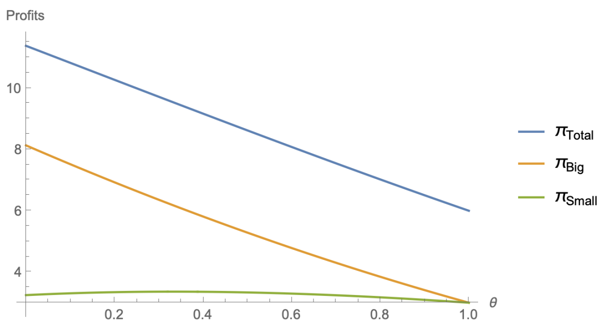

Figure 4: Profits

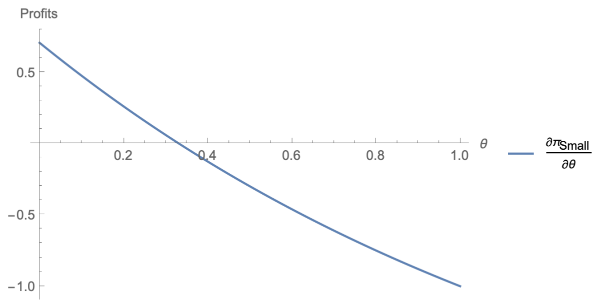

Figure 5: Profit variations of Platform 2

Regarding user surplus, we observe in Figure 6 that it is increasing in θ and convex. The reason is that with interoperability, users benefit from reaching all users from the other platform without paying the transportation cost and the subscription fees of the other platform. The increase is of lower magnitude for low levels of interoperability as some users first-homing on Platform 1 start to second-home on Platform 2, which implies an increase in transportation costs and subscription fees for them.

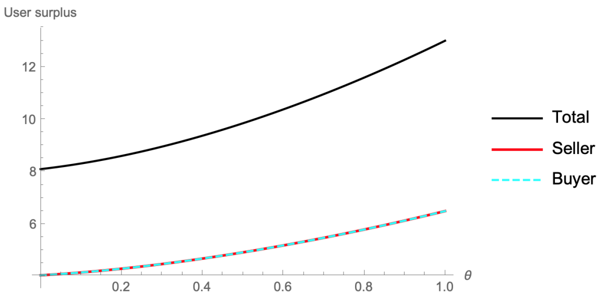

Figure 6: Users surplus

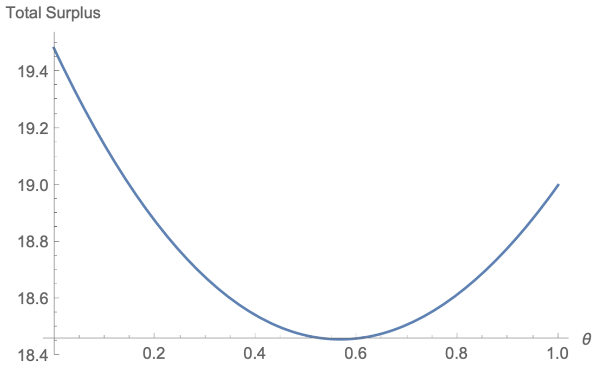

Figure 7: Total surplus

Finally, we find in Figure 7 that total surplus is decreasing for θ lower than 0.55 and increasing for higher levels of interoperability. It thus appears that the decrease in firms' profits, driven by the decrease in Platform 1's profit, is of a higher intensity than the increase in user surplus for low to intermediate levels of interoperability, after which the increase in user surplus dominates.The choice of the optimal level of interoperability to implement for a regulator willing to maximise total surplus thus seems to boil down to either no or complete interoperability. For the parameter values we choose in our graphical example, total surplus is maximised with no interoperability, but for other parameter values, the regulator would find it optimal to set full interoperability.

Therefore, if platforms could decide unilaterally on the level of interoperability, Platform 1 would choose no interoperability, while Platform 2 would choose an intermediate level of interoperability.

From a regulatory perspective, the optimal level of interoperability on the market depends on the objective. If it maximises user surplus, the regulator should set the maximum level of interoperability. If it maximises the possibility of entry, the regulator must choose an intermediate level of interoperability that maximises the profit of the Platform 2. Finally, if it maximises total surplus, the regulator must choose either zero or complete interoperability depending on parameter values.

6 Conclusion and future research

We have shown that interoperability leads users to choose their preferred platform in terms of services, reducing the need to coordinate with other users. This instrument promotes competition between digital platforms by neutralising the effects of market monopolisation and encourages platforms to compete on product quality. This regulatory instrument makes digital markets more contestable and restores competition on the merits. The optimal level of interoperability to implement on the market depends on the objective of the regulator.

The results obtained in our model, where all sides are symmetric, are not particular to two-sided platforms, and apply to one-sided networks. This stems from the fact that, as found by Bakos and Halaburda (2020), in equilibrium with partial multihoming on both sides, the price set by a platform on one side does not affect its demand on the other side. Thus, platforms set their price for each side independently.

We wish to pursue this research project in several directions. First, we are extending the model to integrate data portability. We want to understand the relationship between these two instruments (are they substitutes or complements?) and how one can affect the other. A second research path is to enrich the model by allowing firms to innovate on their standalone value or how users communicate within one platform. A question that arises is how the incentives to innovate for firms is affected by interoperability. Finally, one could also study the case where implementing interoperability is costly, and market participants must share investments. In this setting, the question of the allocation of costs between platforms or by the regulator (i.e. consumers) arises.

Appendix

3.A Assumptions

3.A.1 Profit equilibrium conditions

Second-order conditions for profit maximisation should hold, and equilibrium profits should be positive. This requires $\frac{4\tau^2}{(\tau^2-\alpha^2)(\tau^2-\alpha^2(1-\theta)^2)} > 0$ and$-\frac{2\tau}{\tau^2-\alpha^2(1-\theta)^2} < 0$, respectively. These two conditions ares equivalent to $\tau^2 > \alpha^2$ and $\tau^2 > \alpha^2(1-\theta)^2$. As $0 < \theta < 1$, the first condition is the most restrictive one.

3.A.2 Participation equilibrium conditions

In equilibrium, we want partial multihoming and full market coverage on the unit interval of both sides. Partial multihoming on both sides at the equilibrium is achieved if $0 < \hat{x}_i^{1*} \leq \hat{x}_i^{2*} < 1$ for $i \in \{S, B\}$, with multihoming users being located between $\hat{x}_i^{1*} \leq \hat{x}_i^{2*}$.

The location of the indifferent users are defined by:

$$\begin{aligned}
\hat{x}_i^{1*} &\equiv \hat{x}_S^{1*} = \hat{x}_B^{1*} \\
&= 1 - \frac{\tau}{2}\left(\frac{2\beta\rho + \alpha(2+\delta)(1-\theta)}{(2\tau - \alpha(1-\theta))(\tau + \alpha(1-\theta))} - \frac{\alpha\delta(1-\theta)}{(2\tau + \alpha(1-\theta))(\tau - \alpha(1-\theta))}\right) \\
&= \frac{(2\tau + \alpha(1-\theta))(\tau - \alpha(1-\theta))\left(\tau(2\tau - \beta\rho) - \alpha^2(1-\theta)^2\right) + \alpha^2\delta(1-\theta)^2\tau^2}{(2\tau + \alpha(1-\theta))(\tau + \alpha(1-\theta))(\tau - \alpha(1-\theta))(2\tau - \alpha(1-\theta))} \\
\hat{x}_i^{2*} &\equiv \hat{x}_S^{2*} = \hat{x}_B^{2*} \\
&= \frac{\tau}{2}\left(\frac{2\beta\rho + \alpha(2+\delta)(1-\theta)}{(2\tau - \alpha(1-\theta))(\tau + \alpha(1-\theta))} + \frac{\alpha\delta(1-\theta)}{(2\tau + \alpha(1-\theta))(\tau - \alpha(1-\theta))}\right) \\
&= \frac{\tau\left((2\tau + \alpha(1-\theta))(\tau - \alpha(1-\theta))(\beta\rho + \alpha(1-\theta)) + \alpha\delta(1-\theta)\left(2\tau^2 - \alpha^2(1-\theta)^2\right)\right)}{(2\tau + \alpha(1-\theta))(\tau + \alpha(1-\theta))(\tau - \alpha(1-\theta))(2\tau - \alpha(1-\theta))}
\end{aligned} \tag{21}$$

These formulas are positive and with a positive denominator thanks to the constraint $\tau > \alpha$. As the participation constraints on each side are the same, we can focus on the constraints on one side only. These participation conditions are:

$$\begin{aligned}
&\hat{x}_i^{1*} > 0 \Leftrightarrow \delta(\alpha\tau(1-\theta))^2 > (2\tau + \alpha(1-\theta))(\tau - \alpha(1-\theta))\left(\tau(\beta\rho - 2\tau) + (\alpha(1-\theta))^2\right) \\
&\hat{x}_i^{2*} < 1 \Leftrightarrow \delta\alpha\tau(1-\theta)(2\tau^2 - (\alpha(1-\theta))^2) < (2\tau + \alpha(1-\theta))(\tau - \alpha(1-\theta))\left(\tau(2\tau - \beta\rho) - (\alpha(1-\theta))^2\right) \\
&\hat{x}_i^{1*} < \hat{x}_i^{2*} \Leftrightarrow 2\tau(\tau - \beta\rho) \leq \alpha(1-\theta)(\tau(1+\delta) + \alpha(1-\theta))
\end{aligned} \tag{22}$$

3.B Proofs

3.B.1 Prices

The effect of interoperability on the prices of the large platform and the small platform are:

$$\frac{\partial p_i^{1*}}{\partial\theta} = \frac{\alpha\left(2\tau + (\alpha(1-\theta))^2(\alpha(1-\theta)(4\tau-\alpha(1-\theta)) + \tau(\beta\rho-2\tau)) - \delta\left(8\tau^4 - \alpha^2(1-\theta)^2\left(10\tau^2-\alpha^2(1-\theta)^2\right)\right)\right)}{\left(4\tau^2-\alpha^2(1-\theta)^2\right)^2}$$

$$\frac{\partial p_i^{2*}}{\partial\theta} = \frac{\alpha\left((\alpha(1-\theta)+2\tau)^2(\tau(\beta\rho-2\tau)+\alpha(1-\theta)(4\tau-\alpha(1-\theta))) + 8\alpha\delta(1-\theta)\tau^3\right)}{\left(4\tau^2-\alpha^2(1-\theta)^2\right)^2}$$

When the number of captive users δ is below the threshold $\bar{\delta}$, the price of the large platform decreases with interoperability; beyond the threshold, it increases:

$$\begin{aligned}
&\frac{\partial p_i^{1*}}{\partial\theta} < 0 \Leftrightarrow \delta > \bar{\delta} \equiv -\frac{(2\tau+\alpha(1-\theta))^2(\tau(2\tau-\beta\rho)-\alpha(1-\theta)(4\tau-\alpha(1-\theta)))}{8\tau^4-\alpha^2(1-\theta)^2\,(10\tau^2-\alpha^2(1-\theta)^2)} \\
&\frac{\partial p_i^{1*}}{\partial\theta} > 0 \Leftrightarrow \bar{\delta} > \delta
\end{aligned} \tag{23}$$

When the number of captive users is below the threshold $\bar{\bar{\delta}}$, the price of the small platform increases with interoperability; beyond the threshold, it decreases:

$$\begin{aligned}
&\frac{\partial p_i^{2*}}{\partial\theta} < 0 \Leftrightarrow \delta < \bar{\bar{\delta}} \equiv \frac{(2\tau+\alpha(1-\theta))^2(\tau(2\tau-\beta\rho)-\alpha(1-\theta)(4\tau-\alpha(1-\theta)))}{8\tau^3\alpha(1-\theta)} \\
&\frac{\partial p_i^{2*}}{\partial\theta} > 0 \Leftrightarrow \bar{\bar{\delta}} < \delta
\end{aligned} \tag{24}$$

When the number of captive users δ is high enough (i.e., $\bar{\bar{\delta}} < \delta$ and $\bar{\delta} < \delta$), an increase in interoperability implies that the large platform lowers its price, $\frac{\partial p_i^{1*}}{\partial\theta} < 0$, and the small platform increases its price, $\frac{\partial p_i^{2*}}{\partial\theta} > 0$.

The second derivative of the level of interoperability on prices is always negative:

$$\begin{aligned}
&\frac{\partial^2 p_i^{1*}}{\partial^2\theta} = -\frac{2\alpha^2\tau\left((2\tau+\alpha(1-\theta))^3(\beta\rho+2\tau)+2\alpha\delta(1-\theta)\tau\left(12\tau^2+\alpha^2(1-\theta)^2\right)\right)}{\left(4\tau^2-\alpha^2(1-\theta)^2\right)^3} < 0 \\
&\frac{\partial^2 p_i^{2*}}{\partial^2\theta} = -\frac{2\alpha^2\tau\left((2\tau+\alpha(1-\theta))^3(\beta\rho+2\tau)+4\delta\tau^2\left(4\tau^2+3\alpha^2(1-\theta)^2\right)\right)}{\left(4\tau^2-\alpha^2(1-\theta)^2\right)^3} < 0
\end{aligned} \tag{25}$$

3.B.2 Participation

The effect of interoperability on the participation on the large platform and the small platform are:

$$\frac{\partial n_i^{1*}}{\partial\theta} = -\alpha\tau\frac{(2\tau+\alpha(1-\theta))^2(\tau-\alpha(1-\theta))^2(\tau(2\tau-\beta\rho)+\alpha(1-\theta)(2\beta\rho+\alpha(1-\theta)))+\delta\left(8\tau^6-\alpha^2(1-\theta)^2\left(2\tau^2-\alpha^2(1-\theta)^2\right)\left(\tau^2+\alpha^2(1-\theta)^2\right)\right)}{\left(4\tau^4-\alpha^2(1-\theta)^2\left(5\tau^2-\alpha^2(1-\theta)^2\right)\right)^2}$$

$$\frac{\partial n_i^{2*}}{\partial\theta} = -\alpha\tau\frac{(2\tau+\alpha(1-\theta))^2(\tau-\alpha(1-\theta))^2(\tau(2\tau-\beta\rho)+\alpha(1-\theta)(2\beta\rho+\alpha(1-\theta)))-\alpha\delta(1-\theta)\tau\left(8\tau^4-2\alpha^4(1-\theta)^4\right)}{\left(4\tau^4-\alpha^2(1-\theta)^2\left(5\tau^2-\alpha^2(1-\theta)^2\right)\right)^2} \tag{26}$$

When the number of captive users δ is above the threshold $\underline{\delta}$, the participation to the large platform decreases with interoperability; beyond it decreases:

$$\frac{\partial n_i^{1*}}{\partial\theta} \le 0 \Leftrightarrow \delta \ge \underline{\delta} \equiv -\frac{(2\tau+\alpha(1-\theta))^2(\tau-\alpha(1-\theta))^2(\tau(2\tau-\beta\rho)+\alpha(1-\theta)(2\beta\rho+\alpha(1-\theta)))}{8\tau^6-\alpha^2(1-\theta)^2(2\tau^2-\alpha^2(1-\theta)^2)(\tau^2+\alpha^2(1-\theta)^2)}$$

When the number of captive users δ is above the threshold $\underline{\underline{\delta}}$, the participation to the small platform decreases with interoperability:

$$\frac{\partial n_i^{2*}}{\partial\theta} \le 0 \Leftrightarrow \delta \le \underline{\underline{\delta}} \equiv \frac{(2\tau+\alpha(1-\theta))^2(\tau-\alpha(1-\theta))^2(\tau(2\tau-\beta\rho)+\alpha(1-\theta)(2\beta\rho+\alpha(1-\theta)))}{\alpha(1-\theta)\tau(8\tau^4-2\alpha^4(1-\theta)^4)}$$

3.B.3 Profits

Let us define:

$$A \equiv \left(2\tau^2-\alpha^2(1-\theta)^2\right)(\beta\rho+\alpha(1+\delta)(1-\theta))-\alpha(1-\theta)\tau(\beta\rho+\alpha(1-\theta))$$

$$B \equiv (2\tau+\alpha(1-\theta))^2(\tau-\alpha(1-\theta))\left(\alpha^2(1-\theta)^2(\beta\rho+\tau)+\tau(\tau-\alpha(1-\theta))(\beta\rho-2\tau)\right)-\delta\tau^2\left(8\tau^4-5\alpha^2(1-\theta)^2\left(2\tau^2-\alpha^2(1-\theta)^2\right)\right)$$

$$C \equiv (\alpha(\theta-1)-2\tau)(\tau-\alpha(1-\theta))(\alpha(\theta-1)-\beta\rho)-\alpha^2\delta(1-\theta)^2\tau$$

$$D \equiv (\tau-\alpha(1-\theta))(\alpha(1-\theta)+2\tau)^2\left(\alpha^2(1-\theta)^2(\beta\rho+\tau)+\tau(\tau-\alpha(1-\theta))(\beta\rho-2\tau)\right)+\alpha\delta(1-\theta)\tau\left(8\tau^4-\alpha^2(1-\theta)^2\left(4\tau^2+\alpha^2(1-\theta)^2\right)\right)$$

We have:

$$\frac{\partial\pi^1}{\partial\theta} = 4\alpha\tau\frac{AB}{(4\tau^2-\alpha^2(1-\theta)^2)^3(\tau^2-\alpha^2(1-\theta)^2)^2}$$

$$\frac{\partial\pi^2}{\partial\theta} = 4\alpha\tau\frac{CD}{(4\tau^2-\alpha^2(1-\theta)^2)^3(\tau^2-\alpha^2(1-\theta)^2)^2}$$

1. There are two scenarios in which $\frac{\partial\pi^1}{\partial\theta} > 0$.
    - In the first scenario $\frac{\partial\pi^1}{\partial\theta} > 0$ when A and B are both positive.

This leads to:

$$\frac{\left(\alpha(1-\theta)\tau-\left(2\tau^2-\alpha^2(1-\theta)^2\right)\right)(\beta\rho+\alpha(1-\theta))}{\alpha(1-\theta)\left(2\tau^2-\alpha^2(1-\theta)^2\right)}<\delta<\frac{\alpha^2(1-\theta)^2(\beta\rho+\tau)+\tau(\tau-\alpha(1-\theta))(\tau-\alpha(1-\theta))(\alpha(1-\theta)+2\tau)^2(\beta\rho-2\tau)}{\tau^2\left(8\tau^4-5\alpha^2(1-\theta)^2\left(2\tau^2-\alpha^2(1-\theta)^2\right)\right)}$$

- In the second scenario, $\frac{\partial\pi^1}{\partial\theta}>0$ when A and B are both negative.

2. There are two scenarios in which $\frac{\partial\pi^2}{\partial\theta}>0$.

- In the first scenario, $\frac{\partial\pi^2}{\partial\theta}>0$ when C and D are both positive. This leads to:

$$\frac{(\tau-\alpha(1-\theta))(2\tau+\alpha(1-\theta))^2\left(\tau(\tau-\alpha(1-\theta))(2\tau-\beta\rho)-\alpha^2(1-\theta)^2(\beta\rho+\tau)\right)}{\alpha(1-\theta)\tau\left(8\tau^4-\alpha^2(1-\theta)^2\left(4\tau^2+\alpha^2(1-\theta)^2\right)\right)}<\delta<\frac{(2\tau+\alpha(1-\theta))(\tau-\alpha(1-\theta))(\beta\rho+\alpha(1-\theta))}{\alpha^2(1-\theta)^2\tau}$$

- In the second scenario, $\frac{\partial\pi^2}{\partial\theta}>0$ when A and B are both negative.

3.B.4 User surplus

User surplus is given by:

$$\begin{aligned}Surplus =&\beta(1-\rho)-(2+\delta)(\tau-\alpha\theta)-\alpha\\&+2\tau\frac{\tau^2\left(\beta^2\rho^2-\alpha^2(1-\theta)^2\right)+(2+\delta)\tau\left(4\tau^3+\alpha(1-\theta)\left(\tau(\beta\rho+4\tau)-\alpha^2(1-\theta)^2\right)\right)+2\alpha\beta\rho(1-\theta)(\tau+\alpha(1-\theta))(2\tau-\alpha(1-\theta))}{2((\tau+\alpha(1-\theta))(2\tau-\alpha(1-\theta)))^2}\\&+\alpha^2\tau^3\delta^2(1-\theta)^2\frac{4\tau^4-\alpha^2(1-\theta)^2\left(3\tau^2-\alpha^2(1-\theta)^2\right)}{2((\tau+\alpha(1-\theta))(\tau-\alpha(1-\theta))(2\tau+\alpha(1-\theta))(2\tau-\alpha(1-\theta)))^2}\end{aligned}$$

As the surplus on each side is the same, we can focus on the surplus on one side only.

$$\begin{aligned}\frac{\partial Surplus}{\partial\theta}=\alpha(2+\delta)-\frac{\alpha^2\delta^2(1-\theta)\tau^3\left(2\tau^2+\alpha^2(1-\theta)^2\right)}{2(2\tau+\alpha(1-\theta))^3(\tau-\alpha(1-\theta))^3}&+\frac{\alpha(\beta\rho+(2+\delta)\tau)(\alpha(1-\theta)(2\beta\rho+(34-\delta)\tau)-2\tau(5\beta\rho+2(20+\delta)\tau))}{27(2\tau-\alpha(1-\theta))^3}\\&+\frac{\alpha(2\beta\rho-(\delta+2)\tau)(2\alpha(1-\theta)(\beta\rho-(7-\delta)\tau)+\tau(8\beta\rho-(\delta+20)\tau))}{54(\tau+\alpha(1-\theta))^3}\end{aligned}$$

3.B.5 Total surplus

Total surplus is given by:

$$\begin{aligned}&Totalsurplus=\\&2\frac{\tau^3\left(4\alpha\theta\tau+3\beta^2\rho^2+4\beta(1-\rho)\tau\right)-\alpha(1-\theta)\left(\tau^3(-\alpha(\theta+3)-2\beta(3\rho+2)+4\tau)-\alpha(1-\theta)\left(\tau\left(-3\alpha\theta\tau-2\beta^2\rho^2+\beta(5\rho-3)\tau\right)+\alpha(1-\theta)(\alpha(1-\theta)(\beta(1-\rho)-\alpha(1-2\theta))+\tau(5\tau-2(\alpha+\beta(2\rho+1))))\right)\right)}{(2\tau-\alpha(1-\theta))^2(\alpha(1-\theta)+\tau)^2}\\&+2\alpha\delta\frac{\left((1-\theta)\left(\alpha(1-\theta)\left(\tau^2(\tau-3\alpha\theta)-\alpha(1-\theta)(\tau(2\alpha+2\beta\rho-\tau)+\alpha(1-\theta)(\tau-\alpha\theta))\right)+\tau^3(4\alpha+3\beta\rho)\right)+4\theta\tau^4\right)}{(2\tau-\alpha(1-\theta))^2(\alpha(1-\theta)+\tau)^2}\\&+\alpha^2\delta^2(1-\theta)^2\tau\frac{12\tau^6-\alpha^2(1-\theta)^2\left(17\tau^4-\alpha^2(1-\theta)^2\left(9\tau^2-2\alpha^2(1-\theta)^2\right)\right)}{(\alpha(1-\theta)+2\tau)^2(2\tau-\alpha(1-\theta))^2(\alpha(1-\theta)+\tau)^2(\tau-\alpha(1-\theta))^2}\end{aligned}$$

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Conclusion and perspectives

The digital dimension is recent in the history of humanity, but it is profoundly changing the reference system of time and space for humans. Economic activities have naturally been deployed in this new space and have developed services indispensable for many people.[10] It also comes with several socially harmful dynamics.

To correct potential market failures, the regulatory and competition rules of the physical world are gradually being transposed to the new digital space. However, some rules have to be adapted or created from scratch to cope with the emergence of new problems. In this thesis, we investigated two specific issues regarding regulation and law enforcement raised by new artificial intelligence technologies and the emergence of global digital platforms.

The first issue is the definition and enforcement of a regulatory framework for artificial intelligence technologies. Indeed, these technologies can cause damage to individuals, and firms do not necessarily have sufficient incentives to reduce them.

In Chapter 1 of this thesis, I developed with Xavier Lambin a model to study the effects of different regulatory frameworks on firms' choices of artificial intelligence technologies. We have shown that the regulatory framework must consider the specificities of AI technologies and the strategic behaviour of firms and regulators. On the one hand, firms face a trade-off between investing in explainability to benefit from reduced compliance costs and strategically reducing explainability to decrease the regulatory pressure they face. This decision depends crucially on the regulatory environment in which a firm operates. On the other hand, the regulator may also behave in an opportunistic way by choosing to audit firms that have invested in explainability, as the damage is easier to detect. In this case, a firm anticipating this behaviour will tend to reduce its investment in explainability.

Our results contribute to the debate on the implementation of regulation of artificial intelligence. We have defined which regulatory framework should be preferred according to the characteristics of artificial intelligence (e.g., its risk of damage, the AI technology costs), as well as the strategic behaviour of the actors involved. When explainability has hardly an effect on the detection of damage by the regulator, a regulatory framework specific to the technology should be considered (i.e., the level of explainability observed determines the frequency of auditing). The firm can thus use its investment in explainability to signal to the regulator that it will be compliant. Conversely, where explainability strongly affects the effectiveness of detection by the regulator but does not strongly affect the compliance costs of firms, technology-neutral regulation (i.e., the same audit frequency for all technologies) should be preferred to avoid excessive regulatory opportunism.

[10] As an example, the median Internet user would require compensation of \$17,530 to give up search engines for one year. The equivalent estimates for email and digital maps are \$8,414 and \$3,648, respectively (Brynjolfsson et al. (2019)).

Under-enforcement of AI regulation can lead to significant harm. AI regulatory issues are particularly complex in practice, and all available tools should be mobilised to address the risks of AI harm. First, the work of regulators could be facilitated by having privileged access to the tools, methods and databases used by firms. Other tools could be implemented, such as a change in the burden of proof requiring firms to demonstrate the absence or limited likelihood of harm caused by their AI tools. Making firms responsible for demonstrating their innocence would strengthen incentives for explainability, and technology-specific regulation would reinforce these incentives. For many AI applications, however, this tool seems disproportionate. Second, all stakeholders could be mobilised to limit harm. Firms using AI technology should have the possibility to apply to voluntary compliance programs, such as leniency. Finally, those potentially impacted by the potential damage of AI could also be involved in a vigilance role with access to privileged tools to facilitate their detection capacity.

Over-enforcement of AI regulation could also end up harming the very users that regulation is meant to protect. In particular, it may highlight not only the real damage generated by AI but also the potential damage that it may generate. By fueling distrust of these technologies, it could have the effects that firms abandon AI technologies. Robinson and Acemoglu (2012) mention several cases where governments and powerful interest groups have opposed new technologies, with disastrous consequences for economic growth.

The second issue addressed in this thesis relates to the challenge of regulating digital platforms. Digital markets have specificities, explored in Section 2 of the Introduction, which generate concentration dynamics, and lead to entranched dominant positions difficult to challenge. Faced with this situation, many policymakers and commentators propose drastic reforms. In this thesis, we have explored two topics concerning the competition and regulation of digital platforms: coopetition and interoperability.

The second chapter of this thesis develops a model to study cooperation between competing platforms. Regulators do not always have the relevant data to filter between good and bad cooperation. I study the case in which two two-sided platforms can agree on the price to be set on one side of the market but remain in competition on the other side. I show that the platforms internalise that reducing their price on the side where they cooperate will harm the rival platform by making it less attractive to users on that side of the market (e.g., sellers) and, through indirect network effects, to users on the second side as well (e.g., buyers). As a result, cooperation leads platforms to increase their subscription price on the side where they cooperate compared to case where competition is at play on both sides.

However, as sellers gain value (by paying more for their subscription), the competition between platforms to attract buyers intensifies and pulls sellers to join their platform. This leads to lower prices for buyers. I find that coopetition leads to a reduction in profits for firms compared to a purely competitive situation. Thus, it is unlikely that such a strategy, even if it were allowed, would be used by rational firms. However, there may be situations in which firms have found themselves in such a situation. For example, it would appear that this practice was implemented in the meal voucher case studied by the French Competition Authority. Semi-collusion by meal voucher issuers (i.e., the platforms) led to higher prices on the cooperative side and lower prices on the competitive side. My model helps to draw a boundary between situations where coopetition between platforms can increase total surplus. In particular, I show that price coopetition in a market where new users can join the platform can increase total surplus.

The balance between the potential benefits and risks of cooperation on price levels does not seem to favour allowing this type of practice. On the contrary, cooperation on price caps in the digital economy is one of the solutions that might be particularly relevant for regulators. Indeed, Rey and Tirole (2019) show that this solution requires little information for the regulator and, when well designed, they can increase total surplus. Research on cooperation between platforms should particularly look in this direction, through experiments and empirical studies in particular.

Chapter 3 considers interoperability as a regulatory solution to enable new entrants to compete with established platforms. With Guillaume Thébaudin, I built a model to study the effects of interoperability between two platforms with different user bases. The large platform (e.g., the incumbent) has captive users, and the small platform (e.g., the entrant) does not. Interoperability allows users to interact directly with users from the other side that are present on the other platform.

The question addressed is what is the "right" level of interoperability. We show that the level of interoperability to be set by a regulator depends on its objective. If it maximises user surplus, it is optimal to implement full interoperability, as users benefit from interacting with all other users in the market by staying on their preferred platform. In a context where the small platform has not yet entered the market, and the regulator wishes to maximise the probability of entry instead, setting an intermediate level of interoperability – which maximises the profit of the entrant platform – would be optimal. Lastly, the level of interoperability that maximises total welfare is either full interoperability or zero interoperability, depending on the parameter values.

The challenge of reducing barriers to entry for new innovative firms is essential and goes hand in hand with making it easier for users to switch providers. Thus, one of the avenues to be explored in future research is the interplay between interoperability and data portability. Another issue to be explored is the dynamic effects of the implementation of interoperability. Indeed, the incentives of firms to innovate are affected by interoperability.

Interoperability is a powerful tool to mitigate the market power resulting from network effects. However, mandating interoperability may entail several risks and costs that should not be overlooked. For example, determining an interconnection standard, even an open standard, can be particularly time-consuming and costly. Moreover, mandatory interoperability should be used proportionally and take into account the platform function. In particular, firms that cannot guarantee data security and safety should not be allowed to interoperate.

The European digital market act seems to impose some interoperability between platforms.[11] However, it remains unclear how this rule will apply in practice.

Recently, the Chinese government decided to require the major Chinese digital players, Tencent and Alibaba, to interconnect. Both companies have already started to make the necessary changes to make this measure effective. It will be interesting to observe the effects of this evolution on innovation dynamics and user behaviour.

Interoperability may also be a handy policy tool for the Internet of Things. A report from the European Commission estimates that competition is lacking in these markets, mainly because third-party device producers are blocked from interoperating with proprietary operating systems and voice assistants (e.g., Amazon Echo uses Amazon's Alexa voice assistant and not Siri). The report mentions the possibility that these two separate "choke points" could be made interoperable.[12]

Finally, the digital world is rapidly changing and the understanding of economic mechanisms is not always progressing fast enough. However, even with some delay, this collective effort of understanding mechanisms through scientific reasoning and facts is essential and can make the world a better place. As the well-known mathematician Henri Poincaré said, "It is far better to foresee even without certainty than not to foresee at all." More research needs to be done.

[11] Each core platform service must "allow business users and providers of ancillary services access to and interoperability with the same operating system, hardware or software features that are available or used in the provision by the gatekeeper of any ancillary services." (DMA, Article 6.1(f)).

[12] European Commission, Preliminary report, *Sector inquiry into consumer internet of things*, June 2021.

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Résumé de thèse en français

L'essor des activités économiques dans le monde numérique a rapidement contribué à la mise en place de nouveaux services, désormais considérés comme essentiels pour accéder à l'information, communiquer, faire commerce ou se divertir. Mais ce développement est également à l'origine de nouvelles problématiques qui découlent des caractéristiques même de l'économie du numérique (e.g., le numérique facilite la collecte et l'utilisation des données). C'est pourquoi de nouvelles règles s'y sont progressivement instituées (e.g., le règlement général de la protection des données personnelles).

Dans cette thèse, deux défis sont explorés. Le premier est lié à la mise en œuvre de la régulation en présence de technologies d'Intelligence Artificielle. Le second est lié à la régulation du pouvoir de marché des grandes plateformes numériques.

La mise en oeuvre de la régulation en cas d'utilisation de technologies d'IA (Chapitre 1). Le premier défi relève donc de la mise en œuvre de la régulation en cas d'utilisation de technologies d'Intelligence Artificielle (IA). Cette problématique provient notamment du fait qu'une entreprise optant pour une technologie d'IA fait face à un arbitrage entre la performance de sa technologie (e.g., sa capacité à fournir une bonne prédiction) et son explicabilité, c'est-à-dire sa capacité à expliquer son processus de décision en termes humains (e.g., comment la technologie a-t-elle décidé de prédire un résultat plutôt qu'un autre). En l'absence d'un cadre réglementaire approprié ou de réactions effectives des consommateurs, les entreprises ont plutôt tendance à choisir la performance de la technologie plutôt que son explicabilité. Pourtant, ces technologies peuvent générer des résultats inattendus et préjudiciables mais qui peuvent être difficiles à détecter sans une compréhension fine du processus de décision de la technologie. Les entreprises n'ont pas forcément les incitations suffisantes pour réduire ces dommages. La problématique est alors de concevoir un cadre réglementaire qui permet de promouvoir l'investissement en explicabilité afin d'améliorer la détection de dommages.

Pour répondre à cette question, nous développons avec Xavier Lambin un modèle dans lequel un régulateur cherche à réduire, par la menace d'audit, le risque de dommage généré par l'utilisation de technologies d'intelligence artificielle par une entreprise. Le régulateur cherche également à limiter ses coûts de régulation. L'entreprise peut alors fournir des efforts pour améliorer sa conformité en réduisant le risque de dommage (e.g., avec des dispositifs d'audit interne) ou prendre le risque de se voir infliger une amende en cas de détection de mauvaise conduite de sa technologie par le régulateur. L'entreprise peut investir dans l'explicabilité pour mieux comprendre sa technologie et ainsi lui faciliter l'identification des risques de dysfonctionnement. Cependant, une technologie plus explicable peut également faciliter la détection d'une mauvaise conduite par le régulateur et ainsi augmenter l'efficacité de ses audits. Nous comparons la mise en œuvre de deux cadres réglementaires. Dans le premier cadre, le régulateur maintient la même fréquence d'audit pour toutes les technologies quel que soit leur niveau d'explicabilité. Dans le second cadre, le régulateur observe le niveau d'explicabilité et ajuste sa fréquence d'audit en conséquence.

Ce modèle permet de déterminer quel cadre réglementaire privilégier selon les caractéristiques de l'IA (son risque de dommage, sa performance et son coût d'explicabilité), et les effets de l'explicabilité sur les comportements stratégiques de l'entreprise et du régulateur. En particulier, lorsque l'explicabilité de la technologie n'affecte pas l'efficacité des audits, une politique d'audit qui s'ajuste au niveau d'explicabilité doit être privilégiée. En effet, elle induit davantage d'investissement en explicabilité et une conformité plus forte de la part de l'entreprise. Le mécanisme en œuvre est que l'entreprise aura tendance à investir en explicabilité pour signaler au régulateur son engagement à être en conformité, afin de préempter un possible audit de la part du régulateur. Cela permettra au régulateur de diminuer sa fréquence d'audit et donc de réduire son coût de régulation. Inversement, lorsque l'explicabilité facilite la détection d'une mauvaise conduite par le régulateur, l'entreprise va s'engager dans une stratégie d'opacification de sa technologie. En effet, dans ce cas, le régulateur a plus de facilité à détecter les dysfonctionnements d'une technologie plus explicable et aura par conséquent une propension plus importante à la contrôler. L'entreprise anticipant ce comportement diminuera l'explicabilité de sa technologie pour réduire la pression réglementaire. Dans ce cas, un cadre de régulation imposant des contraintes plus importantes sur les comportements du régulateurs et l'entreprise doivent être mises en place. Des normes d'explicabilité minimales pourraient notamment être nécessaires dans cette situation. La régulation du pouvoir de marché des grandes plateformes numériques

La régulation du pouvoir de marché des grandes plateformes numériques. Le second défi abordé dans cette thèse est celui de la régulation du pouvoir de marché des grandes plateformes numériques. Il y a en effet une préoccupation croissante que la position de grandes plateformes numériques (e.g., Google ou Facebook) ne puisse plus être contestée par des entreprises plus innovantes, en particulier à cause d'effets de réseau. Ces grandes plateformes sont particulièrement efficaces, notamment dans la gestion des effets de réseau, mais cette absence de contestabilité leur confère un pouvoir de marché important avec la capacité d'imposer des prix élevés, de dégrader la qualité des produits ou de diminuer l'innovation. Dans cette thèse nous avons exploré deux pistes pour corriger cette dynamique. La première est de permettre une coopération entre plateformes concurrentes. La seconde est la mise en place de l'interopérabilité entre plateformes.

La coopération entre plateformes concurrentes (Chapitre 2). Le premier instrument est la coopération entre plateformes concurrentes, que l'on dénomme par un néologisme « coopétition ». En présence d'effets de réseau, un monopole est généralement plus efficace dans la gestion des effets de réseau que plusieurs entreprises. En effet, le monopole tient compte de tous les effets de réseau du marché lorsqu'il prend ses décisions alors que les entreprises ne prennent en compte qu'une partie. Mais une position de monopole produit aussi une inefficacité économique par les rentes qu'elle peut générer. Une solution possible pour combiner une bonne gestion des effets de réseau de l'ensemble du marché sans le pouvoir de marché du monopole pourrait être d'avoir simultanément une situation de coopération entre entreprises, afin de leur permettre d'internaliser l'ensemble des effets de réseau du marché, et de concurrence entre ces mêmes entreprises, afin de limiter le pouvoir de marché ainsi acquis par leur coopération. La problématique est alors de savoir si le bien-être social peut être amélioré, et dans quelles conditions, par cette stratégie de coopétition par rapport à une situation de concurrence ou de monopole.

Pour répondre à cette question, j'ai utilisé un modèle dans lequel deux plateformes symétriques facilitent l'interaction de deux types d'utilisateurs, des vendeurs et des acheteurs, dans une situation où des vendeurs peuvent souscrire à une ou deux plateformes alors que les acheteurs ne peuvent souscrire qu'à une seule plateforme. De nouveaux acheteurs peuvent rejoindre le marché. Les utilisateurs perçoivent ces plateformes comme différenciées horizontalement à la Hotelling. Ce modèle comporte deux périodes. Dans la première période, les plateformes fixent simultanément les prix des souscriptions pour chaque côté du marché. Dans la seconde période, les utilisateurs des deux côtés choisissent simultanément de souscrire ou non aux services proposés par les plateformes. J'étudie ce modèle dans deux environnement différents. Dans le premier environnement, les plateformes se font concurrence sur les prix de souscription des vendeurs et des acheteurs. Le second environnement correspond à une situation de coopétition dans laquelle les plateformes se coordonnent sur le prix de souscription des vendeurs et se font concurrence sur le prix de souscription des acheteurs.

Le principal résultat est que la coopétition étudiée dans ce modèle ne peut augmenter le bien-être social seulement si de nouveaux acheteurs rejoignent le marché. Cette augmentation n'est pas due à une meilleure gestion des effets de réseau mais à une intensification de la concurrence. En effet, en coopérant pour fixer le prix de souscription des vendeurs, chaque plateforme internalise l'externalité négative qu'elle exerce sur l'autre plateforme lorsqu'elle réduit son prix. Cela conduit les plateformes à augmenter le prix de souscription pour les vendeurs par rapport à la situation de concurrence. Dans le même temps, à mesure que la valeur économique des vendeurs augmente, comme les acheteurs exercent un effet de réseau positif sur les vendeurs, la concurrence entre plateformes pour attirer les acheteurs s'intensifie. Ce qui conduit à une baisse du prix de souscription pour les acheteurs. L'intensification de la concurrence peut être telle que les plateformes peuvent se retrouver avec un profit moindre dans une situation où elles coopèrent que dans une situation de concurrence totale. Dans ce modèle, ce n'est pas une meilleure gestion des effets de réseau qui peut améliorer le bien-être social mais l'intensification de la concurrence.

L'interopérabilité entre plateformes (Chapitre 3). L'interopérabilité est le second instrument étudié dans ma thèse pour allier une bonne gestion des effets de réseau tout en évitant la monopolisation du marché par une seule plateforme. Internet a été conçu comme un réseau interopérable entre des systèmes ouverts. Un exemple de ces débuts est l'interopérabilité entre les services de courrier électronique, où les utilisateurs de gmail et de wanadoo peuvent s'envoyer des courriels. Mais, aujourd'hui, l'écrasante majorité des services de messagerie instantanée comme Facebook messenger utilisent des protocoles propriétaires et les utilisateurs ne peuvent pas envoyer de messages d'un service de messagerie à l'autre (e.g., de WhatsApp à Signal). Cette situation conduit les utilisateurs à souscrire à un service selon le niveau de participation des autres utilisateurs et pas forcément selon le service dont la valeur intrinsèque leur conviendrait le mieux. Cela peut engendrer une dynamique de monopolisation du marché et d'importantes barrières à l'entrée. Cette problématique est présente avec la même acuité pour les plateformes bifaces, comme les plateformes d'intermédiations de e-commerce. L'interopérabilité améliore la contestabilité en neutralisant les effets de réseau dans le choix de l'utilisateur et donc les problèmes de coordination avec les autres utilisateurs. La problématique est alors de savoir quel serait le niveau optimal d'interopérabilité entre les plateformes bifaces selon les différentes parties prenantes.

Pour répondre à cette question, nous avons développé avec Guillaume Thébaudin un modèle où deux plateformes asymétriques facilitent l'interaction de deux types d'utilisateurs, des vendeurs et des acheteurs qui peuvent souscrire à une seule plateforme ou aux deux plateformes. L'asymétrie entre ces deux plateformes provient du fait qu'elles ont des bases d'utilisateurs différentes. La grande plateforme a des utilisateurs captifs, acquis par une présence passée sur le marché, alors que la petite plateforme n'a pas d'utilisateurs captifs. L´ interopérabilité permet aux utilisateurs d'une plateforme d'interagir avec les utilisateurs de l'autre côté du marché présents sur l'autre plateforme. Par exemple, les vendeurs de la grande plateforme peuvent interagir avec les acheteurs de la petite plateforme. Notre modèle comporte deux périodes. Dans la première période, les plateformes fixent simultanément les prix des souscriptions de chaque côté du marché. Dans la seconde période, les utilisateurs des deux côtés choisissent simultanément de souscrire ou non aux services proposés par les plateformes. Nous analysons les effets de différents niveaux d'interopérabilité entre plateformes pour les différentes parties prenantes. Différents niveaux d'interopérabilité peuvent être interprétés comme différents niveaux de qualité d'interconnexion ou de possibilité d'utiliser toutes les fonctionnalités d'interconnexion (e.g., le transfert d'images ou de vidéos).

Ce modèle permet de mettre en lumière les effets de l'interopérabilité sur les décisions de multihébergement des utilisateurs. Le niveau optimal d'interopérabilité à fixer par un régulateur dépend de son objectif. S'il veut maximiser le surplus de l'utilisateur, alors il est optimal de mettre en œuvre une interopérabilité totale, car les utilisateurs bénéficient de l'interaction avec tous les autres utilisateurs du marché en restant sur leur plateforme préférée. Si le régulateur veut maximiser la probabilité d'entrée, alors la fixation d'un niveau d'interopérabilité intermédiaire - qui maximise le profit de la plateforme entrante - serait optimale. Pour des niveaux faibles d'interopérabilité la petite plateforme voit une augmentation de demande de la part des utilisateurs. Par ailleurs, ce modèle confirme un résultat déjà bien établi dans la littérature selon lequel la mise en place de l'interopérabilité est toujours néfaste pour la grande plateforme. Enfin, le niveau d'interopérabilité qui maximise le bien-être total est soit l'interopérabilité totale, soit l'interopérabilité nulle, selon les valeurs des paramètres. Le profit perdu par les entreprises est plus important que le bénéfice perçu par les utilisateurs. Ces premiers résultats ouvrent la voie à plusieurs approfondissements et notamment sur les effets dynamiques de la mise en place de l'interopérabilité et la comparaison de l'interopérabilité avec d'autres instruments permettant d'augmenter la contestabilité du marché comme la portabilité des données.

Pour conclure, l'économie numérique génère des bénéfices immenses mais également des problématiques qui nécessitent la mise en place d'un cadre de régulation adapté et d'une politique de la concurrence vigoureuse. Cette thèse contribue au débat sur la mise en place de ce cadre dans deux domaines. Le premier correspond au nouveau défi posé par l'utilisation de l'intelligence artificielle. Notre modèle avec Xavier Lambin met en lumière les nouvelles difficultés que l'IA peut engendrer pour la mise en place d'un cadre réglementaire et propose plusieurs recommandations pour la mise en place d'un tel cadre. Le second explore deux mécanismes visant à une bonne gestion des effets de réseau tout en évitant la monopolisation du marché par une seule plateforme. Le premier moyen étudié était de permettre aux plateformes une meilleure gestion des effets de réseaux en coopérant afin de leur permettre d'internaliser les différents effets de réseau dispersés dans le marché. Cependant nous trouvons que la coopétition peut effectivement augmenter le bien-être social mais pas en raison d'une meilleure gestion des effets de réseau mais d'une intensification de la concurrence. Le second moyen est l'interopérabilité entre plateformes qui permet effectivement de partager les effets de réseau à l'ensemble du marché et de neutraliser le pouvoir de marché issu des effets de réseau, mais dont on peut s'interroger sur les effets dynamiques de la mise en place d'un tel instrument.

ECOLE
DOCTORALE

Titre : Régulation et politique de la concurrence à l'ère numérique : Essais en économie industrielle

Mots clés : antitrust, plateformes numériques, régulation, algorithmes

Résumé : Cette thèse aborde deux enjeux auxquels les régulateurs doivent faire face dans l'économie numérique : le défi informationnel généré par l'utilisation de nouvelles technologies d'intelligence artificielle et la problématique du pouvoir de marché des grandes plateformes numériques.

Le premier chapitre de cette thèse étudie la mise en place d'un système d'audit (coûteux et imparfait) par un régulateur cherchant à réduire le risque de dommage généré par les technologies d'intelligence artificielle et à limiter ses coûts de régulation. Les entreprises peuvent investir dans l'explicabilité de leurs technologies pour mieux comprendre leurs algorithmes et, ainsi, réduire leur coût de conformité à la réglementation. Lorsque l'explicabilité n'affecte pas l'efficacité des audits, la prise en compte du niveau d'explicabilité de la technologie dans la politique d'audit du régulateur induit davantage d'investissement en explicabilité et une conformité plus forte de la part des entreprises en comparaison d'une politique neutre à l'explicabilité. Si, au contraire, l'explicabilité facilite la détection d'une mauvaise conduite par le régulateur, les entreprises peuvent s'engager dans une stratégie d'opacification de leur technologie. Un comportement opportuniste de la part du régulateur décourage l'investissement dans l'explicabilité. Pour promouvoir l'explicabilité et la conformité, il peut être nécessaire de mettre en œuvre une réglementation de type "commande et contrôle" avec des normes d'explicabilité minimales.

Le deuxième chapitre explore les effets de la coopétition entre deux plateformes bifaces sur les prix de souscription des utilisateurs. Plus spécifiquement, les plateformes fixent les prix de souscription d'un groupe d'utilisateurs (par exemple, les vendeurs) de manière coopérative et les prix de l'autre groupe (par exemple, les acheteurs) de manière non coopérative. En coopérant pour fixer le prix de souscription des vendeurs, chaque plateforme internalise l'externalité négative qu'elle exerce sur l'autre plateforme lorsqu'elle réduit son prix. Cela conduit les plateformes à augmenter le prix de souscription pour les vendeurs par rapport à la situation de concurrence. Dans le même temps, à mesure que la valeur économique des vendeurs augmente, comme les acheteurs exercent un effet de réseau positif sur les vendeurs, la concurrence entre plateformes pour attirer les acheteurs s'intensifie, ce qui conduit à une baisse du prix de souscription pour les acheteurs. Nous considérons deux scénarios : un marché en croissance (dans lequel de nouveaux utilisateurs peuvent rejoindre la plateforme) et un marché mature. Le surplus total augmente uniquement dans le premier cas, lorsque de nouveaux acheteurs peuvent rejoindre le marché.

Enfin, le troisième chapitre s'intéresse à l'interopérabilité entre une plateforme en place et un nouvel entrant comme instrument de régulation pour améliorer la contestabilité du marché et limiter le pouvoir de marché de la plateforme en place. L'interopérabilité permet de partager les effets de réseau entre les deux plateformes, ce qui réduit leur importance dans le choix de souscription des utilisateurs à une plateforme. L'introduction de l'interopérabilité entraîne une réduction de la demande pour la plateforme en place, qui réduit le prix de son tarif de souscription. En revanche, pour des niveaux d'interopérabilité relativement faibles, la demande pour le nouvel entrant augmente (de même que son prix et son profit), puis celle-ci diminue pour des niveaux d'interopérabilité plus élevés. Dans tous les cas, les utilisateurs bénéficient de la mise en place de l'interopérabilité.

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Title : Regulation and Competition Policy of the Digital Economy: Essays in Industrial Organization

Keywords : Antitrust, Digital platforms, Regulation, Algorithms

Abstract : This thesis addresses two issues facing regulators in the digital economy: the informational challenge generated by the use of new artificial intelligence technologies and the problem of the market power of large digital platforms.

The first chapter of this thesis explores the implementation of a (costly and imperfect) audit system by a regulator seeking to limit the risk of damage generated by artificial intelligence technologies as well as its cost of regulation. Firms may invest in explainability to better understand their technologies and, thus, reduce their cost of compliance. When audit efficacy is not affected by explainability, firms invest voluntarily in explainability. Technology-specific regulation induces greater explainability and compliance than technology-neutral regulation. If, instead, explainability facilitates the regulator's detection of misconduct, a firm may hide its misconduct behind algorithmic opacity. Regulatory opportunism further deters investment in explainability. To promote explainability and compliance, command-and-control regulation with minimum explainability standards may be needed.

The second chapter studies the effects of implementing a coopetition strategy between two two-sided platforms on the subscription prices of their users, in a growing market (i.e., in which new users can join the platform) and in a mature market. More specifically, the platforms cooperatively set the subscription prices of one group of users (e.g., sellers) and the prices of the other group (e.g., buyers) non-cooperatively. By cooperating on the subscription price of sellers, each platform internalizes the negative externality it exerts on the other platform when it reduces its price. This leads the platforms to increase the subscription price for sellers relative to the competitive situation. At the same time, as the economic value of sellers increases and as buyers exert a positive cross-network effect on sellers, competition between platforms to attract buyers intensifies, leading to a lower subscription price for buyers. The increase in total surplus only occurs when new buyers can join the market.

Finally, the third chapter examines interoperability between an incumbent platform and a new entrant as a regulatory tool to improve market contestability and limit the market power of the incumbent platform. Interoperability allows network effects to be shared between the two platforms, thereby reducing the importance of network effects in users' choice of subscription to a platform. The preference to interact with exclusive users of the other platform leads to multihoming when interoperability is not perfect. Interoperability leads to a reduction in demand for the incumbent platform, which reduces its subscription price. In contrast, for relatively low levels of interoperability, demand for the entrant platform increases, as does its price and profit, before decreasing for higher levels of interoperability. Users always benefit from the introduction of interoperability.

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