DIGITAL PLATFORM ECONOMICS: ESSAYS ON INNOVATION EFFECTS, ASSESSMENT OF MARKET POWER, AND POLICY APPROACHES TO PROMOTE COMPETITION

By

Tiago Sousa Prado

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Information and Media – Doctor of Philosophy

2023

ABSTRACT

The rise of digital platforms as a business model and a critical infrastructure for the digital economy is causing increasing trepidation among scholars and competition policy enforcers. In response to concerns about platform dominance, policies that were in place since the 1990s to keep the digital economy free from traditional regulation are being reconsidered. In these discussions, competition is considered an essential mechanism to harness the social and economic benefits of digital platforms, as it serves to attenuate potential risks to innovation, democracy, and to the media industry.

This dissertation contributes to these discussions theoretically and empirically. It addresses three important, interrelated aspects of the debate. Self-contained chapters explore the challenges of designing comprehensive responses to safeguard and promote competition in digital markets. One of the topics investigated is whether digital platforms harm sector innovation by acquiring too many small start-up firms. This analysis uses a unique data set of venture capital, IPO, and M&A activity that includes more than 40 thousand deals reported worldwide between 2010 and 2020. A second topic is the development of an empirically tested, conceptual framework for the assessment of market power in digital markets. The insights gained from exploring these two topics are then integrated into a discussion of alternative options for the design of policy and regulatory regimes that aim at promoting competition *for* and *on* digital platforms.

The empirical analysis of hundreds of big tech start-up acquisitions shows that venture capital funding for innovation increased after the acquisitions analyzed. However, this effect is short-lived and other concerns arise. The findings suggest that a closer review of these mergers by better-equipped competition policy enforcers would be beneficial to deal with the

complexities of digital markets. Although new competition policy instruments may be needed, strict ex ante remedies may not bring the right incentives to promote digital innovation.

The proposed conceptual framework for market power assessment showed the need for new tests in addition to the traditional evaluation of the competitive structure of platform markets. Also, it was possible to conclude that policy remedies, to have significant impact in promoting competition in digital markets, should be enforced jointly in both user- and supplier sides of the platforms. Furthermore, the results of an online survey experiment with 550 participants suggest that an analysis of user responses to different levels of digital ads and data collection procedures bundled with online services would greatly improve assessments of market power.

Finally, the analysis of alternative proposals of competition policy and regulatory regimes for digital markets suggests that carefully designed remedies, that observe country-specific developmental conditions and challenges, are key to effectively promote competition without harming incentives for innovation and investment. The analysis also supports a very limited use of ex ante, policy remedies to boost competition for incumbent digital platforms.

Overall, this dissertation expands scientific knowledge on how the strong benefits of the platform economy can be preserved while protecting competition and the incentives for innovation in digital markets. It develops theoretically and empirically grounded contributions that will help policymakers and regulatory agencies in the development of workable approaches to promote competition in digital markets. It also explores the complementarity of antitrust and regulation, and ways to better orchestrate these instruments with each other and with varying national and regional contexts.

This dissertation is dedicated to Jesus Christ, to whom I belong, to Livia, the love of my life, and to my children Ana Flor, Pedro, and Leo, my true legacies on earth.

ACKNOWLEDGEMENTS

The adventure to pursue my doctoral studies would never have started without the unconditional support of my wife, Livia Prado, who paused her career, and renounced the comfort of our beloved home-country, Brazil, to follow me on this journey. My dear love, thank you for trusting in my dreams, and for persevering through an uncountable number of hours alone, taking care of our children and home while I was working on this research. I am also extremely grateful to my parents, Wagner and Nelcina Prado, to my brother, Paulo Prado and his wife, Amanda Prado, and to my parents-in-law, Arias and Damares Soares, for always encouraging and supporting me to fly higher in life, even when this would mean missing my personal presence.

Moreover, I would like to express my deepest gratitude to Dr. Johannes M. Bauer, my academic advisor. I could not have been under better guidance and support. Thank you for coaching my career and life throughout this four-year-long endeavor. Always available, always supportive, always worthy-to-ask, and always relevant. I also would like to extend my sincere thanks to Dr. Rachel Mourão, Dr. Ruth Shillair, and Dr. Jay Pil Choi, my dissertation committee, who generously provided knowledge and expertise.

Lastly, I would like to extend my sincere thanks to the Agência Nacional de Telecomunicações of Brazil (Anatel), to the Quello Center for Media and Information Policy, and to the Department of Media and Information at Michigan State University. Your financial support was fundamental to encourage me to "go back to school", master new research tools, and contribute to the scientific knowledge, all of this without having to compromise the well-being of my family. I feel truly privileged by God for such an opportunity in life.

TABLE OF CONTENTS

CHAPTER I - INTRODUCTION

The digital technology has transformed people's lives in the last decades. Effects on the way we communicate, work, learn and trade are undeniable. Its enabling effects on competition, investment, and innovation in many industries are also well recognized. On the other hand, the rise of digital platforms as a critical infrastructure and increasingly important business model in the digital economy has been seen with trepidation by a growing number of scholars and competition policy enforcers. Prevailing policies to keep the digital economy free from traditional regulation are being reconsidered. This dissertation contributes with foundational knowledge on how, and to what extent, these developments affect society and current policy regimes for digital networks and services.

During the past decade, traditional instruments of competition policy have been employed. The list of antitrust cases investigating potential, anti-competitive practices of the big, digital platforms such as Google, Facebook, and Amazon, is long and growing. More recently, policy has pivoted to structural responses, exemplified in the approval of the Digital Markets Act (DMA) by the European Union, which introduces a whole framework of competition policy and regulatory measures to promote competition in digital markets. Several legal initiatives have also been introduced in U.S. Congress.

For example, the legislative proposals H.R.3816 – *American Choice and Innovation Online Act*, under discussion in the U.S. House of Representatives, and S.2992 – *American Innovation and Choice Online Act*, under discussion in the U.S. Senate, are aimed at limiting the ability of incumbent intermediation platforms to acquire nascent, technology companies (U.S. House of Representatives, 2021; U.S. Senate, 2021). Legislative proposals to promote more competition in the digital ecosystem are also under discussion in other regions (e.g., Latin America and Asia). For example, the Brazilian parliament is discussing empowering the telecommunications regulator to oversee and take action to protect and promote competition in the digital ecosystem (Câmara dos Deputados do Brasil, 2022).

Apart of potential threats to the efficiency of some digital markets, the dominance of a few big techs in the intermediation business is also being associated with broader ailments of a digitally enabled society. For example, platforms are associated with the increased polarization of the political debate in democratic countries (Krämer, 2017; Gillespie, 2018). The promotion of disinformation, and the lack of transparency on news distribution, with harmful consequences to media trust and quality, also seen as a consequence of the weak competitive pressure exerted on incumbent platforms (e.g., Flew and Martin, 2022).

Some authors assert that in the absence of competitive pressure platforms do not undertake sufficient efforts to remedy flaws in the design of the algorithms governing information flows on their networks (Rolnik et al., 2019). Furthermore, effects to data security, personal privacy, and cybercrimes (e.g., piracy on content distribution) have been associated with the lack of competition in the delivery of digital services (Rosen, 2011; Strahilevitz et al., 2019).

Many authors share the view that competition is essential to harness the social and economic benefits of digital platforms with the expectation that this would attenuate potential risks to innovation, democracy, and to the media industry.[1] For example, Mansell and

[1] Throughout this dissertation, competition is conceptualized as a dynamic process of rivalry among suppliers of goods and services for consumers and their attention. This framing is a generalization of traditional models of competition, such as models of perfect competition, duopoly, or monopoly. It builds on early work on monopolistic competition, the notion of workable competition, theories of contestable markets, and more recent approaches to strategic management in digital markets (e.g., Clark, 1940; Schumpeter, 1942; Hayek, 1949; Baumol, Panzar and Willig, 1982; Tirole, 1988; Laffont & Tirole, 1999; Petit & Teece, 2021). In this perspective, suppliers have numerous options to compete, including prices, quantities, quality, and multiple forms of innovation that may introduce new products and services, new production processes, and designs.

Steinmueller (2020) review the main reasons provided by neoclassical, and institutional economists to intervene in the operation of markets with the goal to promote competition as the most effective check on the behavior of dominant firms. Both frameworks argue that i) the risk of displacement, associated with ii) effective competition push market players to a more efficient use of inputs and a more desirable generation of outcomes. The authors suggest that, informed by these traditional economic theories, policymakers around the world increasingly perceive that the potential harms associated with a high level of concentration in the platform economy are sufficiently serious to require a response.

This dissertation approaches this issue theoretically and empirically and expands the edge of knowledge on the topic by exploring overarching, interrelated questions, that altogether contribute to the main challenge of policymakers and regulatory authorities on designing comprehensive responses to safeguard and promote competition in digital markets. This subject is so big that no single person can cover all the relevant issues. Although much work has been done in the academy and by competition authorities, three important topics remain highly contested: i) the potential harms to innovation and investment resulting from the incumbency advantages accrued by big digital platforms; ii) the market power assessment in digital markets; and iii) how competition can be promoted in digital markets. Ex post, ex ante, and hybrid policy and regulatory instruments are evaluated.

These concerns are examined in this dissertation with the goal to make theory-based, substantive, and practical contributions to the scholarly literature and digital policy practice. The dissertation is structured to explore these topics in separate, specialized chapters. Chapter II develops foundational concepts pertaining the promotion of competition in digital markets. It discusses the main characteristics of two-sided markets, commonly adopted as a successful business model in the digital economy, as well as the rise of big, U.S. digital platforms as dominant platform intermediaries in several digital markets in most countries. Then, it concludes with an analysis of the risks and benefits of platform dominance in digital markets.

Chapter III sheds light on the controversy over the effects of digital platforms on innovation. First, it explores the incentives of incumbent platforms to acquire small start-ups. This chapter builds upon core theories of innovation, some dating back to the debate among scholars arguing in a Schumpeter tradition and Arrow, on the conditions most conducive to innovation (Gilbert, 2020). Specifically, it critically examines the discussion on these controversial claims about the pro- and anti-competitive effects of big tech start-up acquisitions.

An empirical analysis of the effects of big tech platform acquisitions of start-ups on innovation and investment complements the conceptual framework. The study builds on the early management literature on the importance of venture capital to the innovation ecosystem (e.g., Kortum and Lerner, 2000; Baker & Gompers, 2003), on recent developments on the main drivers of venture capital activity (e.g., Gompers et al., 2020), and on potential effects of big tech start-up acquisitions on innovation and funding for start-ups (Foerderer et al., 2018; Kamepalli et al., 2020).

Chapter IV examines the forms and manifestations of market power when a platform has a dominant position in several digital markets. The definition and operationalization of market power in digital markets is an unresolved topic worthy of further advancements. For example, Scott-Morton at al. (2019) and U.K. Treasury (2019) argue that the traditional conceptualization of market power, which relates to the capacity of a firm to increase and sustain prices above the competitive equilibrium, needs to be broadened in the context of digital markets. In these new markets, retail prices are mostly zero. Competitive advantages and entry barriers are created by the accumulation and ownership of customer data as well as information about complementary players.

Also, controversies surrounding the definition of objective, theory-based criteria to identify market power are a current subject of research. For example, Wu (2018) and Petit and Teece (2021) discuss the nuances of the assessment of market power in the platform economy, as well as new tools to be used in the definition of market boundaries when price is not the single form of charging end users for consuming services. The methods to define which digital platforms and markets should be targeted by pro-competitive remedies, either under a competition policy framework or under a regulatory regime, are still not a consensus.

To expand knowledge boundaries and contribute to the topic, a conceptual framework is proposed for the assessment of market power in digital markets. The framework builds on recent developments in industrial organization theory to understand competition in two-sided markets with platform intermediaries (e.g., Rochet and Tirole, 2003; Armstrong, 2006), and on applied approaches, particularly the discrete-choice demand modeling approach proposed by Berry (1994) and Nevo (2000).

Chapter V tests the assumptions made in Chapter IV with an on-line-based, survey experiment with 550 participants. The research contributes to the design of new competition policy, and regulatory instruments to identify market power of digital platforms that play in several markets.

Finally, informed by the results of the research on the potential effects created by big tech start-up acquisitions on funding for innovation, and on the market power assessment in digital markets, Chapter VI presents a comparative institutional analysis of prototypical competition policy and regulatory regimes that are currently suggested in the research literature.

Considerable controversy persists on the advantages and disadvantages of several alternative policy and regulatory regimes designed to deal with concentration and potential anticompetitive misconduct in digital markets.

The Chapter presents a comparative analysis of the advantages and disadvantages of the main policy regimes that are considered to promote competition in digital markets. The analysis begins by differentiating the roles of structural and behavioral remedies to promote competition in digital markets. Following, five regimes currently suggested in the research literature and explored by practitioners are analyzed in detail, ranging from precautionary competition policy and traditional ex ante regulatory remedies to ex post competition policy enforcement, ex post regulation and various self-regulation and co-regulation mechanisms. More specifically, two overarching institutional approaches are analyzed: ex-ante and ex-post policy and regulatory regimes focusing on promoting competition *on* markets served by dominant digital platforms, and regimes aimed at promoting competition *for* these dominant digital platforms (see Crémer et al., 2019).

Then, building on recent developments in competition policy scholarship (e.g., Haucap and Heimeshoff, 2014; Federico et al., 2020; Petit, 2020; Cabral, 2021,), a conceptual analysis of the likely effects of adopting different policy and regulatory regimes is provided. Of particular interest is their appropriateness and efficiency to achieve the different envisioned goals. The analysis suggests that no single best regime exists that can promote competition and innovation in all digital markets alike. Rather, regional and market-specific conditions (e.g., developmental phase of the digital market, landscape of potential players) may require different approaches.

Chapter VII concludes the dissertation by summing up the many ways it pushes the knowledge boundary on the promotion of competition in digital markets, and informs policymakers, regulators, and antitrust agencies. Overall, the dissertation aims at a deeper understanding of how the strong benefits of the platform economy can be preserved while protecting the incentives for innovation and efficiency in the broader digital economy. It helps clarifying the options for the improvement of competition legal and regulatory frameworks that safeguard the benefits of the digital economy, by presenting a theoretically and empirically grounded knowledge on how policymakers and regulatory agencies should act to promote competition in digital markets. It also explores the complementarity of antitrust and regulation, and ways to better orchestrate these instruments with each other and with national and regional contexts.

CHAPTER II – PLATFORM INTERMEDIATION: MAIN CONCEPTS AND CHARACTERISTICS

This chapter introduces ground-level concepts pertaining to the platform economy. It starts with a review of the main characteristics of the platform intermediation business model. Then, it discusses the rise of big digital platforms as dominant players, and it concludes with an analysis of the risks and benefits of platform dominance in digital markets.

2.1. Two-sided digital markets and the rise of platform intermediation

The emergence of big technology companies intermediating the provision of services and goods in many two-sided markets has attracted researchers from different scholarly perspectives, interested in understanding the implications of this new market structure on their fields of study. The earliest studies of two-sided markets date from the 1970s (e.g., see Rosse, 1970), with a long research tradition on the topic among media economic scholars[2]. However, the presently used terminology and the greater attention from other fields arose mainly during the last twenty years. Contributors are primarily from economics and policy (e.g., Rochet and Tirole, 2003; Armstrong, 2006), political communication (e.g., Rosen, 2011; Krämer, 2017; Gillespie, 2018; Van Dijck at al., 2018), engineering (e.g., Helmond, 2015; Spagnoletti et al., 2015), and management (e.g., Pagani, 2013; Tan et al., 2015; Parker and Van Alstyne, 2017; Cusumano et al., 2019).

Internet business model development during the past two decades has been described as the “platformization of the Internet,” which Helmond (2015, p. 1) formally conceptualized as

[2] For an early summary and review see Owen and Wildman (1992).

"the rise of the platform as the dominant infrastructural and economic model of the social web." Immense advances in data processing and storage capacity technologies have created many new business opportunities for dominant digital platforms. Beyond intermediating the communication between internet users and firms, they collect and process a vast amount of information about behaviors, preferences, interests, ideas, knowledge, as well as the physical and psychological traits of their billions of users around the world. They have used such information strategically, for example, to improve their own services, develop new businesses models, anticipate trends, understand the strategies of their competitors, launch new products and services, expand their business to promising markets, and do risk management.

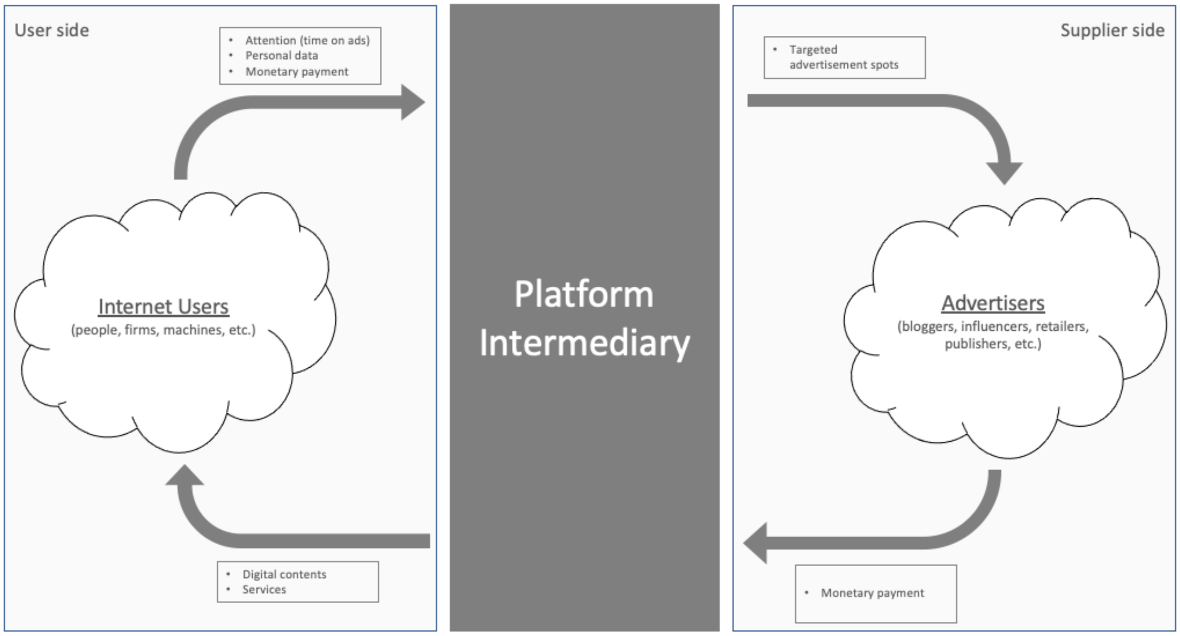
Crémer et al. (2019) differentiate big incumbent digital platforms from other corporations by the strength of direct and indirect network effects derived from their size and multimarket presence, as well as by the economies of scope and scale brought by the intensive use of digital technologies. Digital platforms fundamentally function as intermediators connecting users and suppliers. In such two-sided markets, different sorts of configurations emerge according to the nature of network effects. In most cases, users strongly value the presence of other users (direct network effects), and, in some cases, also the presence of suppliers (indirect network effects).

Also in most cases, suppliers strongly value the presence of users on the other side of the intermediation platform (indirect network effects). Differences in the strength of network effects between the user and supplier side allow intermediation platforms to adopt cross-subsidy schemes between user-side markets and supplier-side markets (Rochet and Tirole, 2003). This important characteristic helps to explain why many digital services are offered to end users for free, while revenue is generated in related markets such as advertising or product sales.

For example, in social media markets, advertisers and publishers typically value the size of platform's user base more than users value the number of ad-suppliers reaching them through the social media platform. In this scenario it is rational for the platform to subsidize the service to end-users, and charge suppliers a positive price, as they extract a lot of value from the access to the end-users on the other side of the intermediation platform.

Furthermore, platforms have an interest in end user data, as it improves their ability to offer better intermediation services to buyers. Commonly, platforms use the information collected from internet users to show them contextual, targeted, digital advertisements ("targeted ads") while they are online (see Figure 2.1). For example, in a very common business case throughout the digital economy, advertisement space is sold by intermediary platforms to advertisers aiming to expose their products more efficiently, to people most likely to purchase them. On the user side of the market, the platform provides digital content and services to internet users in exchange for their attention to targeted ads, their data (personal information and digital traces), and sometimes a monetary payment (subscription price), which is often subsidized. On the supplier side of the market, the platform offers targeted advertisement spots to advertisers of retail goods and services, who pay a monetary price for different types of exposure (e.g., per impression, per action, etc.).

Figure 2.1 – Two-sided business model for the provision of targeted ads



Source: Author.

Of course, many two-sided business models exist that are not ads-based (e.g., ride-sharing services, food delivery, etc.). However, the notion of internet users consuming digital contents and services through platform intermediaries in exchange for their attention, personal data, and in some cases also a monetary payment for access, is applicable to most two-sided business models. In other common business cases, platforms act as hubs with one-stop-shop solutions that save time and money from end-users and buyers, as travel lodging platforms, e-commerce platforms, etc.

In a complementary perspective, Cusumano, Yoffie, & Gawer (2020) explain that big techs not only provide intermediation services to connect customers and sellers in different markets, but they also provide technological tools to support the development and distribution of new services. The authors simplify the tremendous diversity of platforms by distinguishing transaction from innovation platforms. Moreover, several digital platforms operate multiple platforms in parallel and run their business models at different scales (e.g., Hagiu and Wright, 2015). For example, some of them are focused on a specific digital market, like social media or media streaming, and thus have limited capacity to collect data to generate revenues on targeted ads or new services (e.g., Spotify, Twitter, Snapchat, etc.). Others run their platform business models in several digital markets, such as app stores, video streaming, gaming, social media, etc., and thus have the capacity to collect or infer information and affect a greater variety of aspects of internet users' lives.

Indeed, although the notion of *digital platforms* is used generically, they come in many forms and their impact on society varies. Strong positive effects of digital platforms on productivity, and on transaction costs reduction are widely reported (e.g., Kulick, 2021). The emergence of enabling platforms, like operational systems, app distribution services, and cloud-based, hosting services have boosted venture capital investment for innovation in the last decade (see Chapter III). Also, entrepreneurship and tech start-up activity have picked in the last decade due to the low costs of hosting and distributing new applications.

The emergence of social media platforms as a very popular application accessed through smartphones around the world gave room for a relevant process of fragmentation of media production, distribution, and consumption, a development predicted by Chaffee and Metzger (2001). The fragmentation of media outlets gave people more control and ownership on what media content to consume and may have diminished the effects of traditional mass media on society. However, it brought extremely powerful, new mechanisms of media dissemination that are even stronger than the traditional ones to produce change in behaviors, purchase decisions, and political leanings. Moreover, social media also democratized the access to media campaigns, once only on the reach of big corporations. By allowing access to customized, cost-effective media campaigns to small firms, social media has heightened its presence and importance on several economic sectors, producing greater impact on society.

It is also important to recognize the implications of social media for the power that traditional media outlets may have to tell what people should think about (studied by agenda setting theories). Chaffee and Metzger (2001) explained that social media allow society to signal to mass media what individuals are interested in. For example, Russell Neuman et al. (2014) points out that social media have been used by people to discuss social issues (e.g., abortion, drugs, same-sex marriage, political leaning, etc.) more intensely than economic issues and the working of government, themes that are usually preferred by traditional, mass media outlets. Social media platforms have also empowered politics, other influential personalities, and common citizens to be more active in the political debate, as they can use digital platforms to share their discourse and opinions with a broader audience.

2.2. Platform dominance: risks and benefits

Big, incumbent digital platforms benefit to a larger extent than other corporations from strong direct and indirect network effects related to their size and multimarket presence. These advantages are strengthened by economies of scale and scope brought by the intensive use of digital technologies (Crémer et al., 2019). Digital platforms fundamentally function as intermediators connecting users and suppliers, or generally multiple sides of market relationships, with different types of configurations depending on the nature of network effects and the adopted business model. For example, in social media platforms, users strongly value the presence of other users (direct network effects), and, to a lesser extent, the presence of suppliers (indirect network effects). On the other hand, suppliers of ads, goods, and services strongly value the presence of users on the other side of the social media platform (indirect network effects).

Another important example are platforms that coordinate transactions between suppliers and customers, as some media streaming and e-commerce platforms. These platforms design market rules governing price and volume conditions, define possible marketing strategies of sellers, arbitrate the relationship between customers and sellers, and in many ways can be thought of forms of markets (Spulber, 2019). In these platforms, the presence of suppliers (e.g., selling their products or providing their content) is also highly valued by the customers (indirect network effects), which allows many of these platforms to charge a monetary price from users to access the platform.

In fact, the difference in the strength of network effects between the user-side and the supplier side of intermediation platforms allows them to adopt cross-subsidy schemes between user-side and supplier-side market relations (Rochet and Tirole, 2003). This asymmetry helps to explain why many digital services are offered to end users for free. For example, in social media markets, sellers, advertisers and publishers value much more the size of platform’s user base, than users value the number of ad-suppliers reaching them through the social media platform. So, the platform attracts price-sensitive end-users (the majority) by offering services for free or at a low price, while extracting rents from sellers, advertisers, and publishers.

This strategy gave rise to the current concentrated structure of many digital markets. Early-mover, technology-intensive platform intermediaries like Google, Facebook, and Amazon were able to acquire in a few years high levels of market share among users in many digital markets, through the offer of welfare-enhancing, low- to zero-priced services.

Simultaneously (or in some cases later), the platforms recover their investments in infrastructure, needed to acquire a big user base, by extracting surplus from suppliers that are strongly interested in reaching the unique base of billions of end users gathered by the platforms.

Although the rise of big digital platforms has had positive impacts on several dimensions, the increasing dominance of a few of them has heightened concerns among scholars and policymakers on potential harms brought by the concentrated structure of the digital economy. Scott-Morton et al. (2019) and U.K. Treasury (2019) summarize the discussions among scholars and government experts on the potential economic harm created by the lack of competition in digital markets dominated by big, digital platforms. Risks to innovation in the short and long run, and higher mark-ups paid by suppliers to platform intermediaries are of utmost concern. Both would have broad repercussions for the economy.

Platforms could stymy innovation or bias it in directions that favor own operations (e.g., Ezrachi and Stucke, 2022). Claims in this vein range from a potential platform-induced trend towards complementary rather than disruptive innovation, to killing start-up acquisitions with the sole purpose of reduce competition and maintain platform dominance in the long-run (Callander and Matouschek, 2021; Wu, 2018). These, and another recurrent claims, like the potential negative effects of platform start-up acquisitions on venture capital funding for innovation, are investigated in depth in Chapter III.

Another assertion is that higher markups would contribute to higher prices of goods and services to retail consumers or reduce the profit margins of retailers in highly competitive retail markets. Prat and Valletti (2022) consider social media platforms as attention brokers that accumulate proprietary information about their users' product preferences and sell targeted ad space to retail product industries. The authors then demonstrate that the platforms' dominance in digital ad markets leads to concentration and consequently to an increase in the prices of ads. Such an effect, the authors explain, likely harms competition and innovation in retail markets, as incumbents may be in a better position to afford the higher prices of advertisements. In other words, the higher prices of digital ads induced by the concentration in digital ads market create an entry barrier to new, small innovators in retail markets that need to purchase digital ads. In turn, this has negative impacts on consumer welfare.

Besides of concerns about negative effects of platform dominance on innovation and on microeconomic variables, the new communication arrangements brought by digital platforms have heightened a debate among scholars on their implications to the sustainability of western democracies. For example, Young and McGregor (2020) alert to the fact that social media platforms have created the necessary conditions to the propagation of harmful, extremist political propaganda in the United States. The authors explained that, according to earlier studies of Lazarsfeld and Merton (1948), the conditions for the spread of Nazi propaganda in Germany, not present in the United States after the World War II, were i) monopolization, or the absence of counter-messaging, ii) canalization, or the capacity to target audiences based on their preexisting beliefs, and iii) supplementation, or the ability of people to engage in interpersonal communication about the media propaganda.

These conditions, according to Young and McGregor (2020), are now present in the United States thanks to social media platforms. They claim that, although social media increase competition on media distribution, it allows people to be targeted by one-sided discourses (monopolization), reinforced by opaque algorithms that do not allow for the exercise of the right to contradictory. Also, canalization is a central characteristic of social media, that uses algorithms to select which media content should be exposed to everyone individually. Finally, the authors explain that social media facilitates supplementation, as it allows political discussions and expression by any individual, a privilege earlier restricted to those with economic power.

It is important to note that despite the concentrated structure of digital markets, the large accumulation of capital, technology, and data in the hands of few digital platforms may also have benefits. They likely have accelerated the emergence of large-scale innovative digital solutions and have helped meet the growing demand for efficiency and agility in the processes of production, collaboration, and communication that permeate the economy. For example, big techs have built complementary infrastructures that overcome some of the shortcomings of the public Internet regarding service quality and security (e.g., Stocker et al., 2021).

The drastic increase in the demand for digital products and services during the COVID-19 pandemic has highlighted the importance of the robust technology infrastructure provided by the big digital platforms, which was built in a sustained process of capital accumulation and investments. Moreover, large platforms enable welfare enhancing efficiency gains for small businesses, including in the distribution of products and services, channels to reach their customers, and to scale technology solutions. In addition, they help end users to obtain relevant search results in a very short time, what a more fragmented market would hardly allow.

Some scholars reason that the already mentioned special characteristics of many digital markets (strong network effects, economies of scale and scope, as well as the use of new pricing schemes that often result in cross-subsidies between market sides) make them naturally concentrated. For example, early studies reported by Caillaud and Jullien (2003) recognized that, in intermediation markets, concentration may not necessarily result in inefficiencies, as consumer surplus would be well protected in the presence of workable contestability.

Frieden (2018) points out that market concentration could be seen as a reward to those ventures offering desirable digital services, and so governments should accept some aspects of it. Using a similar argument, Dasgupta and Williams (2020) advocate that policymakers should not be concerned with digital markets concentration, as direct and indirect network effects and economies of scale and scope are what generates values and welfare to consumers. Given these structural features of digital markets, the authors argue that instead of adopting measures to encourage the entry of new platform intermediaries, policymakers and competition authorities should focus on managing the consequences of market concentration, to avoid abusive conduct of dominant incumbent platforms.

Whereas some digital markets may be concentrated, a related point is made by Haucap and Heimeshoff (2014), who reason that even dominant firms will be disciplined by a dynamic process of Schumpeterian competition, as non-performing firms will be displaced by rivals. Thus, potential welfare-reducing effects due to anticompetitive conduct must be carefully analyzed and weighed against potential welfare enhancing effects of concentration in digital markets (Calvano and Polo, 2021).

In the next Chapter, one aspect of platform dominance in the digital economy will be explored in further detail, that is its potential effects on incentives for start-up innovation.

CHAPTER III – EFFECTS OF DIGITAL PLATFORMS DOMINANCE ON INCENTIVES FOR INNOVATION

Concerns about the growing dominance of big digital platforms like Google, Facebook, Apple, Amazon, and Microsoft have greatly increased in recent years. Scott-Morton et al. (2019) and U.K. Treasury (2019) summarize the discussions among many scholars and governmental agencies about the potential harms derived from concentration in digital markets. Fundamentally, they focus on risks to innovation in the short and long-run, and in mark-ups paid by suppliers to platform intermediaries and, consequently, higher prices of goods and services to retail consumers or lower profits to retailers in highly competitive markets.

Other scholars bring different perspectives to the discussion. They emphasize that the special characteristics of many digital markets (e.g., strong network effects, economies of scale and scope, as well as the adoption of cross-subsidies) make them naturally concentrated. In such markets, competition often unfolds as Schumpeterian rivalry, where a dominant is contested and by a disruptive innovator that becomes the new dominant firm in the future (Haucap and Heimeshoff, 2014). Although some level of concentration may be welfare enhancing in some markets even in the long run, its benefits should be carefully analyzed against the costs of potential anticompetitive misconduct of incumbent digital platforms with market power (Calvano and Polo, 2021).

Despite this controversy, the belief that concentration of major digital markets has reached a level where it potentially harms innovation is widely shared. A key claim is that quasi-monopolistic platforms have sub-optimal incentives to maintain a high pace of innovation. A related assertion is that big techs defend their market position using an aggressive strategy of acquiring start-up companies (Wu, 2018). The argument holds that the takeover of nascent, very innovative start-ups (and their engineers) is a strategy to preempt competition and guarantee that dominant platforms extract high profits from their innovations for a long period of time. There are also claims that such acquisitions contribute to the creation of "kill zones" for start-ups (Kamepalli et al., 2020). According to the authors, this effect can happen because the presence of a big tech in an industry niche ends up undermining the adoption of start-up innovations by other companies that do not want to rely on technology that is on the verge of being absorbed by a big tech. For similar reasons, the authors argue, venture capitalists stay away from funding entrepreneurship in these industry niches.

Again, there are contrasting positions that conclude that big tech acquisitions serve a useful purpose. First, they allow that welfare enhancing innovations brought by small start-ups, once fueled by the abundant data and capital and the immense user base of the big techs, reach a wider audience faster (Kennedy, 2020). Second, they have a positive impact to overall growing venture investment, as venture capitalists see acquisitions as an important exit strategy for their investments in tech start-ups (Byrne, 2018; NVCA, 2021a).

In this chapter, I empirically examine the effects of acquisitions by "big tech" platforms, such as Google, Amazon, Apple, Facebook, and Microsoft, on venture capital funding to emerging companies. Big techs regularly acquire promising start-up companies ("start-ups") in their early stages of development. The five U.S. big techs have collectively acquired more than 800 start-ups during the past decades (CB Insights, 2021). Recent investigations by antitrust authorities in the United States and Europe of past, big tech, start-up acquisitions have focused attention among scholars and practitioners on the effects of these transactions on competition and innovation (U.S. Federal Trade Commission, 2020; Motta & Peitz, 2021; Varian, 2021; Katz, 2021).

Discussions among venture capitalists, academics, and entrepreneurs suggest that start-up acquisition strategies employed by big techs may have ambiguous short- and long-run effects on innovation (U.S. Department of Justice, 2020). In the short term, big tech acquisitions may discourage VC investment in early-stage start-ups that aim at the same industry segments. Because large digital platforms can imitate innovations quickly, venture capitalists may shy away from investing in companies that directly compete with them. At the same time, the prospect of selling a start-up to big tech platforms offers an attractive exit strategy for VCs to recoup their investment. Other things being equal, this prospect likely boosts their investment in start-ups.

Similar ambiguous effects exist in a longer-term strategic perspective. Big tech acquisitions may be a strategy to reduce the threat that new competitors might emerge and eventually challenge their own business. If acquisitions reduce potential competition, they may, therefore, reduce the innovation incentives among incumbent big techs. On the other hand, consumers might benefit from tools created by early-stage start-ups that are scaled up and integrated by big techs into their digital platform after the acquisition. The net effect of these opposite effects is difficult to discern theoretically and will have to be informed by empirical analyses. Based on a large dataset, this research is a first step toward such an assessment.

This work contributes to an emerging research literature that provides differentiated insights for several industries. The identified effects of acquisitions are typically contingent on specific market conditions (e.g., Letina et al. 2021; Fumagalli et al. 2022). However, very little available empirical work examines these concerns and the overall net outcome for information technology industries. Empirical work about the conditions under which undesirable outcomes might materialize and what could be done to mitigate them is also lacking. This research seeks to narrow this gap by investigating one aspect of this discussion. The focus is on the short-term effects of big tech acquisitions on venture capital funding for start-ups.

For this purpose, a large dataset is analyzed that includes observations on 32,367 venture capital deals and 392 tech start-up acquisitions made worldwide between 2010 and 2020 by Google, Facebook, Amazon, Apple, and Microsoft. Cases in the database come from 173 different industry segments of the tech economy. Controlling for other factors that may influence VC activity, such as initial public offerings (IPOs) and other mergers and acquisitions (M&As), two estimation methods will be employed to estimate the response of VC activity to big tech, start-up acquisitions.

To examine the response of VC activity to an increased level of big tech acquisitions in a given industry segment, a two-way fixed effects Poisson estimation with covariates is employed (Wooldridge, 2010). Then, to assess whether these effects may be causally attributed to big tech acquisitions, use is made of an innovative dynamic differences-in-differences setup. Proposed by Imai, Kim, and Wang (2021), it allows staggered treatment effects and switching treatment status. Findings obtained with fixed effects panel and differences-in-differences estimators reveal a positive, statistically significant, average effect of big tech start-up acquisitions on worldwide, venture capital activity. Positive effects were also found for the United States and Europe.

However, the findings suggest that the effects are transient and fade away after several quarters. Because venture capitalists fund start-ups to enable entrepreneurial innovation, this approach inform the understanding of the repercussions of these acquisitions on the start-up innovation ecosystem. The large number of observations over an extended period unlock insights into historical patterns that are relevant for the design of digital platform policies.

This work is designed to contribute to the research literature and current policy discussions. It demonstrates a feasible empirical strategy to assess the effects of big tech acquisitions on start-up funding for innovation. The results do not provide evidence of a negative short-term effect. They are compatible with suggestions that big tech acquisitions are one of the mechanisms that venture capitalists use to realize a return on investment. Making such acquisitions more difficult may result in less VC investment (e.g., Cabral, 2021). Additional work will be needed to explore longer-term effects. The insights from the research reported here can inform current, competition, policy discussions and help to provide factual grounding to pending legislative and regulatory proposals.

3.1. Venture capital and the funding of start-up innovation

Venture capital is defined as "equity or equity-linked investments in young, privately held companies, where the investor is a financial intermediary who is typically active as a director, an advisor, or even a manager of the firm" (Kortum & Lerner, 1998, p. 3). Venture capitalists' investments are commonly preceded by angel and seed investments that support a firm during its very early development, including pre-operation, market research, product development, and small-scale, product launch phases (Gompers & Lerner, 2004). After a startup has stablished a consistent performance record, such as a growing a user base, a positive cash-flow, and sales growth, it may seek more venture capital to support continued growth.

To mitigate risks, venture capitalists typically follow a staged, capital infusion mechanism (Gompers & Lerner, 2001). The first round of capital infusion to a firm is identified as a Series A investment. Subsequent rounds may occur and are classified as Series B, C, D and E. These rounds of capital infusion often have similar characteristics, because they are aimed at supporting the start-up to scale up and commercialize the innovation. Each new round adds capital from new or incumbent investors in exchange for equity in the firm. The management literature has identified this stage-financing approach and the active role played by venture capitalists on the boards of start-ups in their portfolios as important tools for the success of tech entrepreneurship (Da Rin et al., 2013). In this study, our main goal is to investigate whether and to what extent big tech start-up acquisitions affect this venture capital ecosystem, which provides vitally important support for innovation in the tech industry.

Venture capital and innovation

This research considers the role of VC in providing funding to start-ups for purposes of innovation, broadly defined to include new products and services, new processes, new business models, and the expansion of markets (OECD, 2018). Innovation is difficult to measure directly. Consequently, proxies that measure inputs into the innovation process (e.g., R&D spending) or its outputs (e.g., patents) are typically used (OECD, 2018). The approach adopted here focuses on a broad measure of inputs, namely resources available for entrepreneurial and innovation purposes. There is abundant evidence in the research literature of a close relationship between VC funding and measures of innovation activity, such as patents and research and development (R&D) spending. The direction of this relationship, however, is contested. On the one hand, VC investors are considered “company builders,” who are committed to providing mentorship and capital to emerging entrepreneurs with innovative ideas that have the potential for commercial success (Lerner, 1995; Baker & Gompers, 2003). On the other hand, VC investors may be attracted to financing firms that already have a mature innovation strategy but need capital to scale up, grow, and promise a successful exit option for the venture capitalist in the short to medium term (Bottazzi & Da Rin, 2002). The notion of innovation used here includes market expansion and thus is less sensitive to this issue.

To examine whether venture capital has a causal effect on rates of patenting, Kortum and Lerner (2000) used an external shock on venture capital activity generated by the 1979 "prudent man" reform in pension fund rules, which increased venture capital funding in the United States. Faria and Barbosa (2014) similarly found robust evidence to support a positive, causal effect of venture capital activity on innovation. Between 2000 and 2009, they detected an endogenous, dynamic relationship between VC investment and patent filings observed in seventeen European countries. The authors concluded that this effect resulted from later-stage VC investments, although they provided no details about what they consider early and late-stage VC funding or the theoretical grounds for this finding.

Research by Da Rin and Penas (2007) investigated whether venture capital influences the way companies integrate new knowledge into the innovation process. The authors analyzed the absorptive capacity – "the capacity of a firm to assimilate and exploit new knowledge" – of a sample of nearly 8,000 Dutch firms from 1998 to 2004. Controlling for the selection process that compels venture capitalists to give preference to funding more innovative, promising companies, the authors found that venture capital affected a firm's innovation strategies by directing research and development (R&D) efforts more regularly toward “make” rather than “buy” activities.

A review article by Lerner and Nanda (2020) critically analyzed the state of knowledge about the role played by VC investment to foment innovation. Although the authors recognized the importance of the VC investments to spur innovation, as supported by previous literature, they discussed some limitations of this relationship. First, they argued that a very narrow band of technological innovations fits the requirements of VC investors. These are primarily innovations with a short-term prospect for commercialization. However, such innovations frequently bring limited societal benefits.

Second, Lerner and Nanda claimed that VC investors with deep pockets have a great influence on smaller ones. This influence and the geographic concentration of their headquarters coupled with a lack of diversity in their management teams may create sub-optimal incentives for innovation. For example, they argued that VC investors are more likely to invest in start-ups that are geographically close to their headquarters, creating innovation incentives in areas and sectors far from those with the biggest economic needs. Third, the authors argued that the enormous amount of VC funding available in the 2010s may have resulted in a declining emphasis on governance. The increasing competition among VC funds for investing in the most promising companies may have created room for more “founder friendly” VC deals that contribute less to raising the efficiency of innovative, early-stage start-ups.

Although these limitations are legitimate, the working assumption that venture capital funding is positively related to innovation is not principally challenged by any of them.

Drivers of venture capital activity

Start-up activity is associated with considerable informational asymmetries and uncertainties. Venture capitalists seek to make informed investment decisions to maximize returns under these conditions. Investment decisions are related more to factors, such as the time available to scrutinize firms and the expertise in a specific industry rather than the availability of venture funds (Gompers & Lerner, 2001; Sørensen, 2007). VC investment decisions take into consideration a series of micro aspects of targeted start-up firms, such as the quality of their management team, the industry in which they operate, the level of competition in that industry, the business model, and the product or technology offered.

Gompers et al. (2020) surveyed 885 institutional venture capitalists at 681 firms and concluded that the quality of the management team of the start-up is the most important attribute in VC investment decisions. To value the founders more than the business-related characteristics of start-ups is not a new development in venture investment. In the late 1990s, Feeney et al., (1999) interviewed approximately 150 venture capital investors to understand their investment decision-making processes. The authors found that venture capitalists value "owner" attributes, such as management track-record, integrity, and commitment, more than "business" prospects, such as risk-adjusted potential returns.

An additional, important aspect identified by both Feeney et al. (1999) and Gompers et al. (2020) is the availability of a feasible exit path for the venture investment, either via an IPO or through mergers and acquisitions. The most recent study explains that exits represent the main opportunity for VC investors to return capital to their investors and secure their profit share. A track-record of successful exits is also important for venture capitalists to establish a reputation and attract new investors (Gompers, 1996). Past and recent research suggests that geographic proximity also plays an important role in the investment decisions of VCs, because deals frequently involve post-entry, active monitoring, and board service (Lerner, 1995; Lerner & Nanda, 2020).

Further aspects of the drivers of VC investment were discussed at an event organized by the U.S. Department of Justice (2020). At the event, Ram Shriram, an experienced VC investor and Google Board member, explained:

> *Fundamentally, the way I think about investing is in the person or the team first, then the technology and the defensibility, and then the market space. Because market spaces are fungible over time. It really comes down to how good the team is and whether they're able to pivot if they have to into a different space, morph the company, which all of which is possible early on in the life of a young company.*

Other VC investors in the same workshop supported these views and added new criteria to the VC decision-making process. Kelland Reilly, another experienced VC investor, highlighted the fact that start-up investment decisions consider the scale and density of the data owned by the start-up and how the data are key for its business model. Start-ups that collect data and create feedback loops in which consumers provide data that improve the service and attract more consumers should attract more funding. In his view, this illustrates the current importance of data-driven business models to venture capitalists.

These insights were complemented by VC investors who elaborated on investing in tech markets where platforms are omnipresent. Given this strong presence, start-ups often depend on services provided by the big techs, such as cloud services and map services. However, VC investors are wary about start-ups that rely heavily on platforms because this dependence creates the risk of a single point of failure.

Incentives of incumbent digital platforms to acquire start-ups

To analyze the effects of big tech start-up acquisitions on competition and innovation in the digital ecosystem, it is important to understand the different incentives that incumbent digital platforms have to acquire small, innovative firms. Two seminal theories of innovation incentives help to shed light on this issue, although one must recognize that they are too simplistic and may miss some aspects of innovation in the digital ecosystem. They are the Arrow's "replacement effect", and the Schumpeterian theory of imperfect competition and appropriation of private returns to innovation, discussed by Gilbert (2020) in the context of the digital ecosystem.

The Arrow's theory of "replacement effect" considers that higher profits are generated by innovative processes and goods, when compared to profits generated by using already known technologies. So, firms have incentives to incorporate innovations in replacement to already known products and processes, as this should positively impact their corporate performance. Based on this assertion, the intense acquisition strategy undertaken by incumbent digital platforms should be seen as a rational response of them to a healthy market scenario, where firms have strong incentives to incorporate profit-maximizing technologies. It is worth noting that the big techs are not the biggest acquirers in Silicon Valley, suggesting that their potential strategy of acquiring startups to incorporate their innovations and profit more is aligned with the practice of other big technology corporations.

In a complementary perspective, the Schumpeterian theory of imperfect competition and appropriation of private returns to innovation argues that concentrated markets grant incentives to incumbents that are absent in more competitive markets, as, for example, the means to undertake risky and costly innovations. Also, it may allow incumbents profit for a longer period from their inventions. Under this rationale, the acquisitions of start-ups pursued by the big techs may have the aim of protecting their current market dominant position by "killing off" competitive threats.

It is important to recognize that these two incentives to acquisitions discussed so far are not mutual exclusive. Rather, they may both explain in a great extent the intense start-up acquisition strategy of the big techs (Gilbert, 2020, p. 50). However, while the acquisitions for incorporation of innovative solutions is generally seen by competition policy enforcers as welfare enhancing, the aim of pre-empting competition is viewed with concern, although some scholars claim that the net effects of concentration in digital markets may be positive.

If promoting competition, or even a great level of contestability, for the incumbent digital platforms should be a goal of the merger framework (with a sight on protecting consumer welfare), it should allow the promotion of acquisitions aimed at incorporating innovations, and the discouragement/obstruction of acquisitions aimed at pre-empting competition. At this point, it is important to weigh that, although there have been a lot of claims that big techs systematically acquire small start-ups to shut down innovation projects and kill competitors that would impose risks to their business models and dominant position, no empirical studies have found evidence of a "killer acquisitions" strategy in the tech industry so far (Varian, 2021; Calvano and Polo, 2021).

3.2. Potential Effects of Big tech start-up acquisitions

Acquisitions of start-ups by Google, Facebook, Amazon, Apple, and Microsoft can have several potential positive and negative effects on the likelihood of venture capitalists to invest in a start-up in the same industry segment. First, compared with venture capitalists, digital platforms have access to superior information about consumer markets. Therefore, they should be able to better assess the market potential of an early-stage start-up or an industry segment. In this case, a big tech start-up acquisition would be a positive sign that might attract venture capitalists to invest in start-ups of the same industry segment picked by the big tech. Second, having a resourceful, large-scale, digital platform playing in an industry segment could encourage venture investment in start-ups focused on complementary innovations (Foerderer et al., 2018). Third, a big tech start-up acquisition might increase expectations that the big tech will acquire additional start-ups in the future. This would increase the likelihood that a venture investor will have a successful exit option by selling to the platform (U.S. Department of Justice, 2020).

Furthermore, it is important to recognize that consumers might benefit from tools created by early-stage start-ups that are scaled-up and integrated by big techs into their digital platform after the acquisition. In the long run, this means that a wide audience of consumers and suppliers will benefit from the acquired innovation, that, once fueled by the computational power, capital, and database available at incumbent digital platforms, would allow higher benefits to society than in an opposite scenario.

On the other hand, the competition landscape after the entry of a big tech into a new industry segment through an acquisition might discourage venture investment in other start-ups in the same industry segment.[3] The risk of investing in a start-up might increase after a big tech acquisition in the same industry segment, because start-ups are dependent on a few big techs to host their technological solutions, distribute their apps to end users, and advertise

[3] Although the line of business pursued by some start-ups may be folded after an acquisition, which would decrease competition in this market segment, there is no empirical evidence in the literature to suggest that this happens systematically in the tech industry. In an empirical study of the pharmaceutical industry, Cunningham et al. (2021) found that only 5.3-7.4% of acquisitions in their sample led to a termination of the project.

their products to reach new customers. Moreover, an increased risk that start-ups in related activities might have their products copied by a competing big tech might also stifle venture investment. The overall, net effect of big tech acquisitions will depend on the relative strength of these ambiguous effects and need to be established empirically.

Only a handful of studies have sought to unveil the effects of big tech start-up acquisitions on venture capital activity and on innovation. Kamepalli et al. (2020) argue that tech early adopters, anticipating the integration of an entrant's product by an incumbent platform, have fewer incentives to switch to the entrant's product. This effect reduces the revenue potential of entrants and their competitive positions. It creates "kill zones" for start-ups, who will face considerable struggles to obtain VC funding after a big tech acquisition in their industry segment. The study suggests that drops in the share of VC investment in the industry segments targeted by Facebook and Google major acquisitions, relative to total VC investment in the software industry, provide empirical support for this conceptual claim. The analysis is based on observations of nine selected, very large[4] start-up acquisitions by the big techs in the past twenty years.

Gautier and Lamesch (2021), analyzed data on 175 start-ups acquired by the five main, U.S., big techs between 2015 and 2017. The authors found that most of these start-ups were acquired in their early stage of development and had their product discontinued under its original name. The authors acknowledged that the data available for the study do not allow the exploration and confirmation of the reason behind each start-up acquisition. While fending off potential competition might be in play, other factors are compatible with the observations also. For example, many acquisitions are motivated by an interest in obtaining technological

[4] All acquisitions are valued above US$ 500 million, a scale that puts the acquired companies into a special class of start-ups.

knowledge that can be integrated with other products and services. Thus, discontinuation of a product or brand name does not necessarily signal a negative effect on innovation.

Callander and Matouschek (2021) examined another aspect of the start-up innovation system by looking at the type of innovation. They concluded that start-up innovation driven by the prospects of an acquisition by a larger firm is less disruptive than activities by entrepreneurs and funders not motivated by it. In a scenario in which founders anticipate a sellout to a big tech, they seek to maximize profit pre-acquisition to achieve a higher start-up valuation. This is an interesting observation, but disruption is only one type of innovation and not necessarily the most transformative one. For example, a less disruptive innovation diffused widely by a big tech company may create larger benefits than a more disruptive innovation that is not widely adopted.

Other scholars claim that the intense pace of acquisitions of nascent, tech start-ups by the incumbent digital platforms reduces the number of potential competitors and contestability of digital markets, with long-term harmful effects for the rate and direction of innovation in the digital economy. Scott-Morton et al. (2019) suggests that disruptive innovations are less likely to happen in concentrated markets, and that, although investment in innovation may continue to happen, its type will be fundamentally driven by the incumbent and its commercial strategies.

As argued by one of the participants at U.S. Department of Justice (2020), big tech intensive acquisition strategy could have a median, socially positive outcome, because they foster innovation through increased venture capital activity. However, there are potential downsides in that the mean effect of these activities may not be positive. This could happen if such acquisitions eliminate a “black swan” competitor, a start-up that might evolve into the “next big digital platform”.

Because many start-ups are dependent on a few big techs to succeed, it is plausible to assume that more competition in platform markets, such as social media, app stores, cloud services, etc., should not only bring more innovation to these markets, but also reduce the risk of investing in technology start-ups in other markets. Such a risk-reduction effect would have a positive impact on the entire innovation ecosystem by fostering more start-up creation and VC investment in many niches of the technology industry.

In light of these controversial claims reviewed, competition policy enforcers must weigh the potential positive and negative effects created by the intense big tech start-up acquisition strategy. Such an assessment can inform the design of antitrust remedies aimed at harnessing the positive outcomes and diminishing the negative ones. This suggests that a “one size fits all” solution, such as per se ban of big tech start-up acquisitions as it is currently under discussion at the U.S. Congress would be sub-optimal.

The empirical study presented in this chapter informs these discussions by aiming to discern the broader historical picture. It analyzes the effects of 392 start-up acquisitions made since 2010 by Google, Facebook, Apple, Amazon, and Microsoft in 173 segments of the tech industry. Instead of measuring the variation in the share of VC investment driven to the industry segments that received those acquisitions, we focused on identifying changes in the total number of VC deals and the total amount of VC investment attributable to big tech start-up acquisitions. Furthermore, our empirical approach included as control variables the total number of M&As and IPOs per industry segment, because big tech companies are not necessarily unique or the biggest acquirers of start-ups. The adopted empirical strategy and estimation models are presented in Section 3.4 below.

3.3. Data

The empirical analysis relies on data about venture capital deals, big tech start-up acquisitions, IPOs, and M&As of VC-backed firms that were consummated between January 1, 2010, and December 31, 2020. This information was retrieved from the database gathered by CB Insights.[5] This source classifies each start-up as belonging to twenty economic sectors and hundreds of industries and subindustries. The dataset contains information about a variety of features of each deal, such as the name of the start-up that received the VC funding, its location (continent, country, state, and city), the amount funded in the deal, and the investment round (Series A to E), day, month, and year when each deal was closed.[6] Because of use conditions imposed by CB Insights, the dataset to which we had access includes only information of the two main, tech-related economic sectors: Internet, and Mobile Telecommunications.

These two economic sectors alone comprehend approximately 54% of the total 80,695 VC deals reported by CB Insights between 2010 and 2020. More important, they account for 404 or approximately 70% of the total 582 big tech, start-up acquisitions that occurred in the same period. The big tech start-up acquisitions were heavily concentrated in four of the industries that comprise these two economic sectors: Internet Software & Services, eCommerce, Mobile Commerce, and Mobile Software & Services. In fact, 392 of the 404 big

---

[5] Using a license provided for Michigan State University for research purposes, the data were retrieved from the CB Insights business intelligence platform, available at https://www.cbinsights.com/.
[6] Our dataset does not include information on angel and seed investment, which can be considered the very early stages of venture capital infusion.

tech start-up acquisitions happened in only these four industries. In addition, 32,367 or approximately 40% of all VC deals in this period targeted start-ups of these four industries, representing an investment of more than $750 billion to support innovation by tech-related start-ups.

Because the aim was to identify the effects of big tech start-up acquisitions on VC investment provided to other similar start-ups, we narrowed the analysis and focused on identifying the effects on the subindustry level under these four industries. With this approach, we grouped the 32,367 VC deals and 392 big tech start-up acquisitions into 173 unique, sector-industry-subindustry triads (hereinafter referred to as "industry segments"). The data were analyzed for 44 quarters from 2010 to 2020, for a total of 7612 observations. Appendix I provides further details for each industry segment.

From the CB Insights database, we also retrieved information about the number of IPOs and M&As of VC-backed companies for each industry segment. This allowed us to create fully balanced panel datasets of total VC-deals, VC-funding, big tech start-up acquisitions, IPOs, and M&As of VC-backed companies, per industry segment per quarter for different geographic settings. With the information of total VC deals and amount of VC funding, we could also calculate the average VC funding per deal, industry segment, and quarter. This resulted in an unbalanced panel dataset with observations for the industry segments and quarters with at least one VC deal.

Table 3.1 presents the geographic distributions of deals. We show data of all deals that happened worldwide between 2010 and 2020 as well as information on deals involving only U.S.-based start-ups and those involving only European-based start-ups. The table also provides a breakdown of the variables for industry segments that received no big tech start-up acquisition between 2010 and 2020 (columns labeled as “Untrt”), and those that were affected by at least one acquisition (columns labeled as “Trt”). The table illustrates that VC deals and funding, IPO, and M&A activity are much more intense in treated industry segments of all geographic breakdowns.

Table 3.2 provides descriptive statistics per quarter of all variables for each of the three geographic breakdowns, as well as for all treated and untreated industry segments. It is important to note that the mean number of VC deals and funding per quarter for deals that happened worldwide is greater than the simple sum of the means found for U.S.-only and European-only deals, because the panel dataset containing worldwide deals includes information about many other countries. Table II.1 of Appendix II shows a summary of the distribution of the variables per region. The quarterly development of these variables from 2010 to 2020 across all industry segments is presented in Appendix II (Figures II.1, II.2, and II.3) for each of the three geographic breakdowns.

A quick analysis of Table 3.2 reveals that the average number of VC deals, IPOs, M&As and the amount of VC funding per quarter and industry segment is greater for those industry segments that receive a big tech start-up acquisition at least once. This may suggest the existence of some association between these acquisitions and the VC activity. For example, according to the literature reviewed, big techs and venture capitalists may have similar preferences about the industry segments in which they wish to invest. Also, VC investors may be compelled to invest in start-ups of industry segments previously chosen by a big tech for an acquisition.

On the other hand, we can also note that the average VC funding per deal is higher in untreated industry segments. There are several explanations for this observation. It could imply that start-ups from around the world are less funded in treated industry segments.

Alternatively, it could imply that because treated industry segments have a bigger start-up ecosystem, they allow VC investors to further diversify their portfolios instead of concentrating big amounts of investment in a few start-ups. In the next sections we examine in detail such potential associations and effects.

Table 3.1- VC investment activity in tech-related industries (2010-2020)

Panel:	Worldwide			United States			Europe		
Ind. Segments:	All	Trt	Untrt	All	Trt	Untrt	All	Trt	Untrt
Variables									
VC deals	32367	23726	8641	17238	12662	4576	5342	3676	1666
VC funding	749.3	464.6	284.7	335.4	213.4	122.0	72.4	51.7	20.7
Avg. VC Fun.	23.2	19.6	32.9	19.5	16.9	26.7	13.6	14.1	12.4
Plat. Acqui.	392	392	0	292	292	0	66	66	0
IPOs	1447	1074	373	446	311	135	260	162	98
M&As	6149	4971	1178	3951	3161	790	1118	714	404

Trt columns report descriptive data of treated industry segments only, whereas Untrt reports untreated industry segments only.
Industry segments that received treatment are those that had at least one big tech acquisition between 2010 and 2020.
VC funding is reported in billions of U.S. dollars.
Avg. VC Fun. reports the average amount of funding per VC deal, in millions of U.S. dollars.
Worldwide deals include all VC deals included in the dataset, regardless of the base country of the company that received the VC investment. For information on the distribution of the variables throughout different regions included in the dataset, please refer to Table II.1 in the Appendix II.

Table 3.2 - Descriptive Statistics

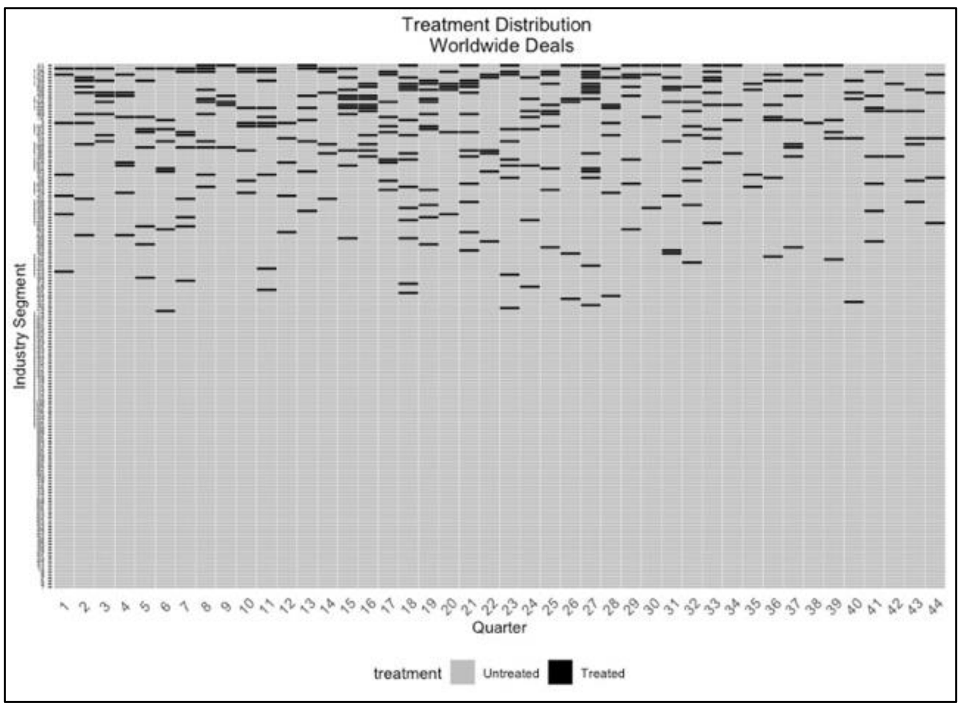
Panel:	Worldwide				United States				Europe			
Variable	Obs	Mean	Min	Max	Obs	Mean	Min	Max	Obs	Mean	Min	Max
VC deals	7612	4.25	0	68	7612	2.26	0	44	7612	0.70	0	21
		(7.82)				(4.47)				(1.67)		
VC funding	7612	98.44	0	14386.99	7612	44.06	0	4100	7612	9.52	0	616.72
		(336.07)				(130.69)				(36.42)		
Avg VC fund.	4647	22.84	0.07	2000	3840	20.62	0.02	1366.67	2282	12.32	0.02	360
		(68.91)				(49.37)				(21.89)		
Platform acq.	7612	0.05	0	5	7612	0.04	0	4	7612	0.01	0	1
		(0.25)				(0.21)				(0.01)		
IPOs	7612	0.19	0	7	7612	0.06	0	4	7612	0.03	0	5
		(0.60)				(0.28)				(0.20)		
M&As	7612	0.81	0	19	7612	0.52	0	13	7612	0.15	0	9
		(1.72)				(1.23)				(0.48)		
Treated industry segments												
VC deals	3608	6.58	0	68	3300	3.84	0	44	1760	0.95	0	17
		(9.36)				(5.80)				(1.66)		
VC funding	3608	128.78	0	14386.99	3300	64.66	0	1591.22	1760	11.76	0	555.50
		(363.33)				(133.75)				(36.17)		
Avg VC fund.	2993	18.18	0.1	1010.42	2372	17.09	0.02	644.18	775	11.83	0.02	360
		(38.69)				(29.87)				(24.75)		
Platform acq.	3608	0.11	0	5	3300	0.09	0	4	1760	0.04	0	1
		(0.35)				(0.32)				(0.19)		
IPOs	3608	0.30	0	7	3300	0.09	0	4	1760	0.06	0	3
		(0.73)				(0.35)				(0.26)		
M&As	3608	1.38	0	19	3300	0.96	0	13	1760	0.23	0	4
		(2.19)				(1.65)	0			(0.54)		
Untreated industry segments												
VC deals	4004	2.16	0	68	4312	1.06	0	34	5852	0.628	0	21
		(5.31)				(2.48)				(1.671)		
VC funding	4004	71.10	0	7373.39	4312	28.29	0	4100	5852	8.843	0	616.72
		(306.95)				(126.06)				(36.472)		
Avg VC fund.	1654	31.28	0.07	2000	1468	26.33	0.07	1366.67	1507	12.57	0.05	291.5
		(102.62)				(69.89)				(20.27)		
Platform acq.	4004	0	0	0	4312	0	0	0	5852	0	0	0
		(0)				(0)				(0)		
IPOs	4004	0.09	0	7	4312	0.031	0	4	5852	0.028	0	5
		(0.42)				(0.20)				(0.186)		
M&As	4004	0.29	0	11	4312	0.18	0	7	5852	0.122	0	9
		(0.85)				(0.57)				(0.456)		

Descriptive statistics calculated per quarter over the 2010-2020 period.
VC funding is reported in millions of U.S. dollars.
Avg VC fund. reports the average amount of funding per VC deal per industry segment per quarter, in millions of U.S. dollars, only considering industry segments and quarters that received at least one VC deal.
Worldwide deals include all VC deals included in the dataset, regardless of the base country of the company that received the

VC investment. For information on the distribution of variables throughout different regions included in the dataset, please refer to Table II.1 in the Appendix II.
Treated industry segments are those that had at least one big tech acquisition between 2010 and 2020.

Figure 3.1 shows the distribution of treated industry segments and quarters (i.e., those that have received at least one big tech start-up acquisition) among all industry segments and quarters included in the dataset. It provides evidence that a given industry segment may have received big tech start-up acquisitions in several quarters during the 2010-2020 period. Big tech start-up acquisitions in the United States and Europe follow a similar pattern. The implications of this characteristic of our data on the estimation procedures are discussed in detail in the next sections.

Figure 3.1 – Distribution of treatment through industry segments and quarters worldwide



3.4. Empirical strategy

The following subsections specify the two empirical approaches that were used to identify the effects of big tech start-up acquisitions on venture capital activity. Section 3.4.1 details a strategy to investigate a potential association between the level (number) of big tech start-up acquisitions in a given industry segment and the level of its VC activity. In addition, Section 3.4.2 presents a strategy to compare VC activity in industry segments that received at least one big tech start-up acquisition (treatment) between 2010 and the end of 2020 with those that did not receive any, to identify the average effect of these acquisitions on VC activity.

Response of VC activity to big tech start-up acquisitions

Consider that an industry segment $i \in I$ receives in each time period $t \in T$ a total amount of venture-capital funding ($vcfund_{i,t}$), through several venture-capital deals ($vcdeals_{i,t}$), to support the creation and delivery of innovative products and services. The average VC funding per deal in a given industry segment *i* and quarter *t* ($avg\_vcfund_{i,t}$) is calculated as the ratio between $vcfund_{i,t}$ and $vcdeals_{i,t}$. The venture capital investment to support innovation may be affected by present or past big tech start-up acquisitions in each industry segment. To model such big tech start-up acquisitions, consider $plat_{i,t}$ as the total number of big tech start-up acquisitions that happened in each industry segment *i* in period *t*. As detailed in Section 3.33.3, the big techs have acquired more than 500 start-ups in the last decade.

As suggested by the literature reviewed in the previous section and considering data availability at the industry-segment level, we control the effect of big tech start-up acquisitions on venture capital activity by other exit events that may have an effect on venture investment, namely the total number of IPOs ($ipo_{i,t}$) and M&As of VC-backed start-ups ($ma_{i,t}$). To differentiate the effect of big tech start-up acquisitions from general exit events, it is important to control for other exit events that may affect venture capital activity. This is because the interest of a digital platform in an industry segment may have a special impact on the risk assessment performed by a venture capitalist before investing in a start-up, as discussed in Section 3.2. In addition, controlling for the number of IPOs per industry segment rules out the effect of time-evolving market scalability of each industry segment on the attractiveness of its start-ups to receive venture investment.[7]

We also control for unobserved industry (c_i) and time-fixed effects (λ_t). c_i accounts for time-invariant characteristics of each industry segment. These include the presence of low sunk costs and high economies of scope and scale that may raise expected payoffs in certain technology-intensive industry segments and thus attract more venture investment. λ_t allows us to rule out the effects of economic cycles and other time-specific, exogenous, economic shocks that may influence venture capital activity, e.g., the COVID-19 pandemic. Based on data availability (as detailed in Section 3.3), our choice for performing the analysis at the industry level does not allow us to control for time-varying, start-up-specific characteristics, such as the experience of its leadership team. The implications of this constraint on our empirical approach to the interpretation of the estimation results are discussed later in Section 3.5.

[7] More IPOs may suggest that the addressable market of start-ups of a given industry segment is big enough to support companies valued at the billion dollar-level, which may attract more VC investment. Gompers et al. (2020) found that past IPOs are an important sign for VC investors, who regard the feasibility of an exit path through an IPO for their investment in a start-up.

Finally, it is important to notice that we foresee a very dynamic relationship between the big tech start-up acquisitions and venture capital activity. Because venture capitalists internalize the new market conditions of the industry segment, the impact of an increased level of acquisitions made by big techs in a certain industry segment may not be visible in the same month or quarter, but only in the near future. To capture these short-run effects, we include in the model three lagged terms of the explanatory variables.[8] Equation (3.1) presents the dynamic equation that we are interested in estimating. The exponential functional form was chosen because both $vcdeals_{i,t}$, $vcfund_{i,t}$, and the average VC funding per deal in a given industry segment i and quarter t ($avg\_vcfund_{i,t}$) receive only zero or strictly positive values. This choice is further discussed in Section 3.5.

$$\begin{aligned} Y_{i,t}^{v} = c_i \varepsilon_{i,t} \exp\,(&\alpha^{v} + \beta_0^{v} plat_{i,t} + \beta_1^{v} plat_{i,t-1} + \beta_2^{v} plat_{i,t-2} + \beta_3^{v} plat_{i,t-3} \\ &+ \boldsymbol{X}_{i,t}\boldsymbol{\gamma}_0^{v} + \boldsymbol{X}_{i,t-1}\boldsymbol{\gamma}_1^{v} + \boldsymbol{X}_{i,t-2}\boldsymbol{\gamma}_2^{v} + \boldsymbol{X}_{i,t-3}\boldsymbol{\gamma}_3^{v} + \lambda_t) \end{aligned} \tag{3.1}$$

In equation (3.1), the dependent variable $Y_{i,t}^{v}$ may be either $vcdeals_{i,t}$, $vcfund_{i,t}$, or $avg\_vcfund_{i,t}$, with the superscript $v = \{vcd, vcf, vcaf\}$ indicating each of three, respectively. The constant α is a cross-sectional and time-invariant mean of the dependent variable, whereas $\varepsilon_{i,t}$ is a specification error term. Furthermore, $\boldsymbol{X}_{i,t-k}\boldsymbol{\gamma}_k^{v} = \gamma_{1,k}^{v} ipo_{i,t-k} + \gamma_{2,k}^{v} ma_{i,t-k}$, for any $k = \{0,1,2,3\}$. The coefficients of interest are β_0^{v}, β_1^{v}, β_2^{v}, and β_3^{v}, the semi-elasticities of $Y_{i,t}^{v}$ with respect to $plat_{i,t-k}$. In other words, they measure the average marginal effect on the venture capital activity in the current and future time periods associated

[8] Although more lagged terms could be included, we opted to limit the empirical investigation to one year (the quarter of the acquisition and three quarters after), because our focus is to identify the short-term effects of big tech start-up acquisitions on VC activity.

with a big tech start-up acquisition that happened in an industry segment i in the current period.

Investigation of causal effects of big-tech start-up acquisitions on venture capital activity

To investigate whether big-tech start-up acquisitions have a causal effect on $vcdeals_{i,t}$, $vcfund_{i,t}$, and $avg\_vcfund_{i,t}$, it is used a dynamic differences-in-differences (DiD) setup with heterogenous treatment effects over time. However, it is important to consider that our treatment (a big tech start-up acquisition in a given industry segment) may happen multiple times over the course of years in the same industry segment, and will have short-term effects (e.g., a few quarters), as the reviewed literature suggests. In other words, our units of analysis (industry segments) may switch from untreated to treated to untreated status multiple times over the course of the observation period.

Because of this switching characteristic of our treatment, well-known dynamic DiD empirical strategies (e.g., Goodman-Bacon, 2018; Athey and Imbens, 2021) cannot correctly identify the average treatment effects of big tech start-up acquisitions on venture capital activity. One alternative would be to investigate only the effects on industry segments that received treatment only once. This would substantively affect the efficiency of our estimation and the robustness of our results, because most of the big tech start-up acquisitions happen in industry segments that have already received treatment in the past. Therefore, to identify the average effects of a big tech start-up acquisition (the treatment) on $vcdeals_{i,t}$, $vcfund_{i,t}$, and $avg\_vcfund_{i,t}$, we utilize the empirical strategy proposed by Imai, Kim, and Wang (2021). This strategy uses matching methods to identify causal inference in panel datasets with switching treatment status. We provide further details of the estimation methods in Section 3.6.

For now, assume $treat_{i,t}$ is a binomial variable that indicates whether the industry segment *i* received treatment in time *t*. Thus, $treat_{i,t}$ equals 1 when $plat_{i,t}$ is greater than zero and equals 0 otherwise. Let *L* be the number of time periods before the treatment during which we want to assure that treated and untreated industry segments have the same history of treatment ($\{treat_{i,t-l}\}_{l=2}^{L}$). For example, if the treatment happened in time *t* = 5, and *L*=3, we would want to compare industry segments treated in *t* = 5 with industry segments untreated in period t=5 but with the same history of treatment in periods *t* = {2,3,4}. Furthermore, consider *F* the number of time periods after the treatment during which one wants to investigate the average treatment effects on the treated units (ATTs). For example, if treatment happened in period *t* and *F*=3, one is interested in investigating the ATTs in periods *t*, *t+1*, *t+2*, and *t+3*. Once defined, these two parameters, *L* and *F*, the dynamic effects that we want to identify can be defined by equation (3.2).[9]

$$\delta^{v}(F,L) = \mathbb{E}\{Y_{i,t+F}^{v}\left(treat_{i,t} = 1, treat_{i,t-1} = 0, \{treat_{i,t-l}\}_{l=2}^{L}\right) \\ -Y_{i,t+F}^{v}\left(treat_{i,t} = 0, treat_{i,t-1} = 0, \{treat_{i,t-l}\}_{l=2}^{L}\right) \big| treat_{i,t} = 1, treat_{i,t-1} = 0\} \quad (3.2)$$

For example, $\delta^{vcd}(2\,,4)$ represents the average difference of the total number of VC deals between a treated industry segment and an untreated industry segment, assessed up to

[9] Details on the selection of *L* and *F* are provided in Section 6.

two quarters after the treatment among matched treated and untreated industry segments with the same history of treatment in in the second, third, and fourth periods before the treatment.

This empirical approach has an intrinsic limitation to identify truly causal effects of big tech start-up acquisitions on VC activity. This is because our data do not allow us to control for all, time-varying factors that may have an effect on VC investment decisions. Our specification assumes that the level of IPO and M&A activity controls the level of attractiveness of each industry segment over time. However, factors, such as the level of expertise of VC investors in a given industry segment or the average quality of the start-up’s management team of each industry segment may also vary over the time but cannot be controlled with the available data. The implications of such limitations on our empirical approach to the interpretation of the estimation results are discussed in Section 3.6.

3.5. Responses of VC activity to big tech start-up acquisitions

Table 3.3 shows results of the two-way fixed effects estimation of the dynamic model specified by equation (3.1), using the entire sample of VC capital deals worldwide between 2010 and 2020. Columns 1, 2, and 3 present estimates for the impact of platform acquisitions on the total number for VC deals per industry segment per quarter. Columns 4, 5, and 6 report estimates for the impact on total VC funding per industry segment per quarter. For brevity, the estimates for the impact of big tech start-up acquisitions on average VC funding per deal and quarter are not reported in Table 3.3. None of them were found to be statistically significant, but they can be reviewed in detail in Table II.2 of Appendix II. Standard errors of the estimates reported in Table 3.3 were clustered at the industry segment level and are robust to heteroskedasticity. Columns 1 and 4 report estimates of the dynamic model of equation (3.1) but without including the controlling variables $ipo_{i,t-k}$ and $ma_{i,t-k}$, for $k = \{0,1,2,3\}$; columns 2 and 5 present estimates with the inclusion of such controlling variables.

Because the dependent variables are non-negative, and hence an exponential estimation model is specified by equation (3.1), we made use of a fixed effects Poisson estimator. One advantage of using a Poisson estimator instead of a linear model is that it allows always to have positive, predicted results. In addition, we do not have to deal with log transformations such as *log(1+y)*, typically implemented to estimate semi-elasticities through linear models when the dependent variable *y* equals zero for some observations (Wooldridge, 2010, p. 723). The results suggest a positive, statistically significant association between platform acquisitions and venture capital activity in the near future (two to three quarters ahead), after controlling for other exit events as well as time- and industry-segment-specific heterogeneity.

Two attractive features of the Poisson estimator are that it allows the assumed Poisson distribution of the dependent variable to be arbitrarily mis-specified, and it permits the presence of any serial correlation (Wooldridge, 2010). However, because the panel dataset includes information from 44 time periods (quarters) and 173 industry segments,[10] columns 3 and 6 present estimates obtained after addressing serial correlation by including multiple lags of the dependent variables among the regressors.[11] Furthermore, as an additional robustness check, we added to the estimation models of columns 3 and 6 forward regressors $plat_{i,t+1}$,

[10] The modern, econometric literature does not consider serial correlation a big issue in a scenario of small T and large N. Because T in our dataset is relatively large (44 quarters), we opted to deal with serial correlation explicitly in the model specification. However, results shown in columns 3 and 6 are not significantly different from those in columns 2 and 5, because the Poisson regressor is robust under serial correlation.

[11] Four lagged dependent variables were included in the model of column 3, whereas only one was in the model of column 6, because any additional lagged terms of the dependent variables were found to be non-statistically significant.

$ipo_{i,t+1}$, and $ma_{i,t+1}$. This procedure allowed us to test the strict exogeneity assumption of the independent variables of our estimation models (Wooldridge, 2010, p. 764). The results, reported in columns (3.F) and (6.F) of Table II.2 of Appendix II, showed no statistically significant effects of current shocks in the level of VC deals and funding on future levels of platform acquisitions per industry segment per quarter.

Table 3.3 – Results of the two-way fixed effects Poisson estimation – Worldwide VC activity

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	VC Deals	VC Deals	VC Deals	VC Funding	VC Funding	VC Funding
Independent variables						
plat	0.0298	0.0183	0.0229	0.0279	0.0187	0.0197
	(0.0317)	(0.0318)	(0.0279)	(0.0762)	(0.0759)	(0.0751)
plat (1 lag)	0.0627	0.0509	0.0474*	0.0734	0.0698	0.0712
	(0.0411)	(0.0397)	(0.0259)	(0.0725)	(0.0792)	(0.0781)
plat (2 lags)	0.0812**	0.0711**	0.0704***	0.195*	0.198*	0.198*
	(0.0346)	(0.0338)	(0.0197)	(0.113)	(0.110)	(0.110)
plat (3 lags)	0.0668**	0.0616*	0.0610***	0.148*	0.119	0.117
	(0.0309)	(0.0323)	(0.0207)	(0.0844)	(0.0839)	(0.0829)
Combined effects						
plat	0.2405*	0.2019*	0.2017***	0.4444	0.4049	0.4057
	(0.1255)	(0.1217)	(0.006)	(0.2729)	(0.2638)	(0.2604)
Observations	7093	7093	6920	7093	7093	7093

Estimation models reported in columns (2), (3), (5) and (6) include current and t-1 to t-3 lagged controlling variables. Estimation model reported in column (3) also include t-1 to t-4 lagged dependent variables for correcting for serial correlation, whereas the estimation model reported in column (6) also include a t-1 lagged dependent variable. Additional lags were not found statistically significant.
Standard errors in parentheses were clustered at the industry segment level and are robust to heteroskedasticity.
* p<0.10, ** p<0.05, *** p<0.01

As the results reported in columns 3 and 6 of Table 3.3 suggest, the semi-elasticities of exit events with respect to the total number of VC deals per industry segment per quarter in the near future are highly statistically significant. But the effects on the total VC funding, although positive on average, are not statistically different from zero at the 5% level in any case. They suggest an increase of 4.74%, 7.04%, and 6.10%, respectively, in the number of VC deals in a given industry segment in the three quarters that follow a quarter in which a big tech start-up acquisition happened in that industry segment. Parameter estimates for the control variables were also statistically significant and can be reviewed in detail in Table II.2 in of Appendix II.

Furthermore, we found a positive combined effect of 20.17% of the platform acquisition on the total number of VC deals from the quarter of the acquisition until the third quarter after an acquisition, with a 95% confidence interval of [5.93%, 34.41%].[12] These results support the claim made in Section 3.2 that a big tech start-up acquisition in a given industry segment produces a positive sign to venture capitalists that increases their interest in investing in start-ups of that industry segment.[13] On the other hand, we found that the combined effect of acquisitions of start-ups by the big techs on the total amount of VC funding in the industry segment that received the shock is not statistically different from zero.

Tables 3.4 and 3.5 show results of similar, two-way, fixed effects Poisson estimation, but using only U.S.-based or European-based VC deals, platform acquisitions, IPOs, and M&As of VC-backed start-ups, respectively. Estimates for the impact on the average VC funding per deal and quarter were omitted for brevity, because they were statistically not significant for either U.S.-based or European-based VC deals, but they are reported in detail

[12] The combined estimate is calculated through the linear combination of the four estimates found for the variables $plat_{i,t-k}$, for $k = \{0,1,2,3\}$.

[13] Section 3.2 suggests three main reasons for an increase in VC activity in response to big tech start-up acquisitions: i) a positive signal of market potential, ii) an increased incentive to VC investment in complementary innovation, and iii) an increased prospect that the big tech will acquire additional start-ups of the same industry segment in the future. However, our dataset and empirical approach do not allow us to make conclusions on which of three factors or which combination of them influence the positive effects found.

in Tables II.3 and II.4 of Appendix II.[14] Standard errors of the estimates reported were also clustered on the industry-segment level and are robust to heteroskedasticity. Furthermore, similar additional robustness checks were performed and suggested that the assumption of strict exogeneity of the regressors strongly holds for the estimation models reported in columns 3 and 6 of both tables. Detailed results of this test and complete results with estimates of all control variables are reported in Tables II.3 and II.4 of Appendix II.

Table 3.4 – Results of the two-way fixed effects Poisson estimation – United States

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	VC Deals	VC Deals	VC Deals	VC Funding	VC Funding	VC Funding
Independent variables						
plat	0.0205	0.00550	0.0161	0.0823	0.0492	0.0317
	(0.0340)	(0.0325)	(0.0263)	(0.0677)	(0.0634)	(0.0604)
plat (1 lag)	0.0971**	0.0789**	0.0786***	0.0999***	0.0782**	0.110**
	(0.0398)	(0.0360)	(0.0245)	(0.0346)	(0.0347)	(0.0474)
plat (2 lags)	0.125***	0.104***	0.0847***	0.306***	0.283***	0.147**
	(0.0351)	(0.0345)	(0.0262)	(0.111)	(0.106)	(0.0608)
plat (3 lags)	0.0606	0.0506	0.0310	0.195*	0.160	0.0179
	(0.0410)	(0.0398)	(0.0307)	(0.102)	(0.0984)	(0.0564)
Combined effects						
plat	0.3031**	0.2385**	0.2105***	0.6835**	0.5701**	0.3071**
	(0.1314)	(0.1205)	(0.0701)	(0.2660)	(0.2339)	(0.1435)
Observations	6519	6519	6201	6519	6519	6201

Estimation models reported in columns (2), (3), (5) and (6) include current and t-1 to t-3 lagged controlling variables. Estimation models reported in columns (3) and (6) also include t-1 to t-5 lagged dependent variables for correcting for serial correlation. Additional lags were not found statistically significant.
Standard errors in parentheses were clustered at the industry segment level and are robust to heteroskedasticity.
* p<0.10, ** p<0.05, *** p<0.01

[14] In the estimation models with no control variables and with control variables, a 47% increase was found on the average VC funding per deal in European-based deals, statistically significant at 10%. However, when we include lagged terms of the dependent variable in the estimation to make it robust to serial correlation, no statistically significant estimates were found.

Table 3.5 – Results of the two-way fixed effects Poisson estimation – Europe

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	VC Deals	VC Deals	VC Deals	VC Funding	VC Funding	VC Funding
Independent variables						
plat	-0.0951	-0.0986	-0.0993	-0.225	-0.264	-0.259
	(0.120)	(0.120)	(0.123)	(0.168)	(0.169)	(0.167)
plat (1 lag)	0.0646	0.0665	0.110	0.680*	0.659*	0.667*
	(0.119)	(0.119)	(0.110)	(0.359)	(0.374)	(0.370)
plat (2 lags)	0.236*	0.248*	0.310**	0.651**	0.666**	0.657**
	(0.143)	(0.149)	(0.153)	(0.302)	(0.312)	(0.316)
plat (3 lags)	-0.104	-0.0964	-0.0720	0.221	0.248	0.241
	(0.140)	(0.147)	(0.143)	(0.377)	(0.382)	(0.382)
Combined effects						
plat	0.1012	0.1193	0.2490	1.3268**	1.3092**	1.3062**
	(0.3449)	(0.3548)	(0.3465)	(0.6258)	(0.6556)	(0.6458)
Observations	5494	5494	5494	5494	5494	5494

Estimation models reported in columns (2), (3), (5) and (6) include current and t-1 to t-3 lagged acquisition variables. Estimation models reported in columns (3) and (6) also include t-1 to t-3 lagged dependent variables to correct for serial correlation. Additional lags were not found statistically significant.
Standard errors in parentheses were clustered at the industry segment level and are robust to heteroskedasticity.
* p<0.10, ** p<0.05, *** p<0.01

The results regarding the effects of big tech acquisitions of U.S.-based start-ups, (found through the most robust estimation models, reported in columns 3 and 6 of Table 3.4) suggest a highly statistically significant, positive impact on both the total number of VC deals and total amount of VC funding per industry segment per quarter in the two quarters that follow an acquisition. The results reveal an average increase of 7.86%, and 8.47% respectively, in the total number of VC deals in a given industry segment in the two quarters that follow a quarter in which a big tech start-up acquisition occurred in a given industry segment. Furthermore, increases of 11.00% and 14.70% in the total amount of VC funding were found in the same period.

The results suggest positive increases of 21.05% and 30.71% in the total number of VC deals and in the total amount of VC funding, respectively, from the quarter of the acquisition until the third quarter after the acquisition, with a 95% confidence interval of [7.31%, 34.79%] and [2.58%, 58.84%], respectively. Although these confidence intervals are wide, they provide empirical ground for the claim that acquisitions of U.S.-based start-ups by the big techs produce positive incentives for innovation in the industry segments of the U.S. tech ecosystem, which receive such acquisitions. Because the big tech start-up acquisitions attract more venture capital to fund other start-ups of that same industry segments, an increased innovation outcome is expected. A vast empirical literature has established a strong, positive, causal relationship between venture capital investment and innovation.

The results presented in Table 3.5 reveal that this positive effect is even stronger in Europe. It displaces claims that associate big tech acquisitions with discouragement for VC investment in other European start-ups playing in the same industry segment. Increases of 11% and 31% in the total number of VC deals were also found in the first and second quarter following the quarter of the acquisition, as reported in column 3 of Table 3.5, although only the impact found in the second quarter is statistically different than zero. On the other hand, the results reported in column 6 reveal strong, positive, statistically significant average increases of 65.90%, and 66.60%, respectively, on the total amount of VC funding in a given industry segment in the two quarters that follow a quarter in which a big tech start-up acquisition happened in a given industry segment. These results suggest a strong positive combined effect of 130.62% on the total amount of VC funding from the quarter of the acquisition until the third quarter after the acquisition, although with a very wide 95% confidence interval of [4.03%, 257.20%].

When compared to the United States, one explanation for a stronger effect of big tech start-up acquisitions in Europe may be the highly dynamic venture capital activity in the latter. VC investors in the United States may have more information about promising industries and start-ups and more options to decide about the allocation of venture funding without using big tech start-up acquisitions as a bellwether.

Finally, our results do not support a clear association between an increase in the number of big tech start-up acquisitions and changes on the average amount of VC funding per deal per quarter in any of the three geographical breakdowns. Thus, although industry segments that have received at least one big tech start-up acquisition between 2010 and 2020 have a lower average VC funding per deal per quarter (as reported in Table 3.2) when compared to untreated industry segments, our findings suggest that this might not happen as a response to an increase in the number of start-up acquisitions performed by the big techs. The lower average funding per deal per quarter in treated industry segments might result from a more diversified start-up ecosystem, as already discussed in Section 3.1, although further research should be done to confirm such a claim.

3.6. Average effects of big tech start-up acquisitions on VC activity

For estimating the average treatment effects of big tech start-up acquisitions on venture capital activity, $\delta^{v}(F, L)$, specified in equation 3.2 of Section 3.4.2, we relied on the estimation procedure proposed by Imai, Kim, and Wang (2021). In summary, for each treated observation, we found a set of control observations with the same treatment history, up to a certain number (L) of time periods before the treatment. After finding a matched set for each treated observation, we used a propensity score weighting (PSW) procedure to estimate a counterfactual outcome for each treated observation, based on the weighted average of the outcomes of the units included in each matched set. Then, we applied the difference-in-differences estimator, using only the outcomes of treated observations and their respective counterfactual outcome.

Identification Assumptions

This estimation approach makes three main assumptions for identifying the ATTs of staggered treatment with switching treatment status. The first assumption is that there are no spillover effects of the treatment. For our study, this requires the assumption to hold that a big tech start-up acquisition in an industry segment does not affect VC activity in other industry segments. Considering that VC funding has been massively available, and that our reviewed literature suggests that VC investors are more constrained by the time to scrutinize different investment opportunities than by the availability of capital, we believe it is reasonable to maintain this assumption for the purposes of this paper with the goal to conduct additional analysis in the future. On the other hand, if this plausible assumption does not hold, the treatment effects identified with this approach may be biased upwards.

The second identification assumption is that the treatment effects on the outcome variable are limited in time (up to L time periods). This assumption is consistent with our empirical data and is supported by the reviewed research literature, which suggests a short-term effect of big tech start-up acquisitions on VC activity.

The third assumption is that, after conditioning on the treatment, covariates, and outcome variable histories (up to L time periods), parallel trends exist between treated and hypothesized counterfactual untreated observations that were very likely to be treated. To maintain this assumption, these counterfactual observations were calculated by adopting a matching procedure with weighting proposed by Imai, Kim, and Wang (2021), as detailed in the next subsections. Equation (3.3) formalizes such a parallel trends assumption.

$$\mathbb{E}\left[Y^{v}_{i,t+F}\left(treat_{i,t}=0, treat_{i,t-1}=0, \{treat_{i,t-l}\}_{l=2}^{L}\right)-Y^{v}_{i,t-1}\middle| treat_{i,t}=1, treat_{i,t-1}=0, \{treat_{i,t-l}, Y^{v}_{i,t-l}\}_{l=2}^{L}, \{ipo_{i,t-l}\}_{l=0}^{L}, \{ma_{i,t-l}\}_{l=0}^{L}\right]$$

$$=\mathbb{E}\left[Y^{v}_{i,t+F}\left(treat_{i,t}=0, treat_{i,t-1}=0, \{treat_{i,t-l}\}_{l=2}^{L}\right)-Y^{v}_{i,t-1}\middle| treat_{i,t}=0, treat_{i,t-1}=0, \{treat_{i,t-l}, Y^{v}_{i,t-l}\}_{l=2}^{L}, \{ipo_{i,t-l}\}_{l=0}^{L}, \{ma_{i,t-l}\}_{l=0}^{L}\right] \quad (3.3)$$

Matching procedure

The first step of the matching procedure was to select the number of time periods *L* before the treatment during which we want to assure that treated and untreated industry segments have the same history of treatment. By choosing *L*, we assume a limited carryover effect of past treatment on the outcome variables (up to *L* time periods). Although a large L makes this assumption less restrictive, it may reduce the chance of finding in the matching procedure controlling industry segments with the same history of treatment as the treated industry segments and potentially yielding less precise estimates. We chose L=3 for coherence with the results of the two-way fixed effects estimation, presented in Section 5, that show a positive, statistically significant, marginal effect of platform acquisitions on VC activity in the first three quarters following an acquisition.

Figure 3.2 – Illustration of the matching procedure for *L*=3

		Time					
		t=1	t=2	t=3	t=4	t=5	t=6
	i=1	0	0	0	0	0	0
	i=2	0	0	1	0	1	0
	i=3	0	0	0	0	0	0
	i=4	0	0	0	0	0	0
	i=5	0	0	0	0	0	0
	i=6	0	0	0	1	0	0
Units	i=7	0	0	0	0	0	0
	i=8	0	0	0	0	0	0
	i=9	0	0	0	0	0	0
	i=10	0	1	0	0	0	0
	i=11	0	0	0	0	0	0
	i=12	0	0	0	0	0	0
	i=13	0	0	0	0	0	1

Note: Each treatment observation, marked as 1, has a set of same time control matched observations, marked as 0 and colored with the same color as the treated observation, which have the same treatment history in the previous two time periods.
Note that, in this example, no control units were assigned for the treatment of observation (i=2,t=5), because none of the control observations of the same time period t=5 have the same treatment history in t=2, t=3, and t=4.

Once L had been defined, we matched treated observations with untreated observations of the same time that had the same treatment history in *t*-1, *t*-2, and *t*-3. This allowed us to build a matched set of control observations for each treated observation. Figure 3.2 illustrates the matching procedure.

Weighting of matched control observations

As proposed by Imai, Kim, and Wang (2021), once the matched sets for each treatment observation had been found, we estimated the ATT of big tech start-up acquisitions on the total number of VC deals per industry segment per quarter, $\widehat{\delta^{vcd}}(F, L)$, on the total amount of VC funding per industry segment per quarter, $\widehat{\delta^{vcf}}(F, L)$ and on the average amount of VC funding per deal per industry segment per quarter, $\widehat{\delta^{vcaf}}(F, L)$. For each treated observation of industry segment *i* and quarter *t*, we estimated the counterfactual outcome $\widehat{Y^{v}_{\iota,t+F}}\left(treat_{i,t} = 0, treat_{i,t-1} = 0, \{treat_{i,t-l}\}_{l=2}^{L}\right)$ by calculating the weighted average outcome of the control observations in each matched set.

We used the well-known, inverse propensity score weighting method (PSW) as proposed by Hirano, Imbens and Ridder (2003). Essentially, based on its propensity score, we calculated a weight for each control observation included in a matched data set. A greater weight was assigned to control observations with a more similar history of covariates ($\{ipo_{i,t-l}\}_{l=0}^{L}$, $\{ma_{i,t-l}\}_{l=0}^{L}$) and outcome values ($\{Y^{v}_{i,t-l}\}_{l=2}^{L}$), compared to the treated observation. In other words, control observations with a propensity score closer to the propensity score of the treatment observation received greater weighting.

This weighting procedure was important to provide support for the pre-treatment parallel trends assumption previously discussed. Other weighting methods, such as the propensity score matching (PSM) procedure, were also tested. They yielded similar results, but with more restrictive assumptions than the PSW method reported, thus supporting our choice of the PSW method.

The propensity score of each matched control observation was calculated as the conditional probability of treatment assignment given pre-treatment values of their covariates and outcome variables, as proposed by Rosenbaum and Rubin (1983). First, we estimated a logistic model of treatment assignment, using for this a subset of data including values of the treatment variable ($treat_{i,t}$) and of all the covariates of interest ($\{ipo_{i,t-l}\}_{l=0}^{L}$, $\{ma_{i,t-l}\}_{l=0}^{L}$, $\{Y^{v}_{i,t-l}\}_{l=2}^{L}$) for all treated industry segments and their matched control industry segments. With these model estimates, we calculated predicted probabilities of treatment conditional on the covariates, which yielded the propensity scores for each treatment and matched control observation. We then assessed the level of similarity between the treatment and control observations, based on the differences in their calculated propensity scores.

Average effects of big tech start-up acquisitions

After we had obtained the weighted, average, counterfactual outcome $\widehat{Y_{i',t+F}^{v}}\left(treat_{i',t} = 0, treat_{i',t-1} = 0, \{treat_{i',t-l}\}_{l=2}^{L}\right)$ for each treatment observation, based on matched observations of industry segments i', we calculated the difference-in-differences estimate $\widehat{\delta^{v}}(F, L) = Y_{i,t+F}^{v} - Y_{i,t-1}^{v} - (Y_{i',t+F}^{v} - Y_{i',t-1}^{v})$ for each of them, and then averaged the results across all industry segments. With this estimation approach, unit-specific fixed effects are ruled out in the difference of outcomes before and after each treatment time. In fact, as reported by Imai, Kim, and Wang (2021) (Theorem 1 at page 11), this DiD estimator is equivalent to the one obtained through a weighted, two-way fixed effects estimation.

This procedure yields the average treatment effect (ATT) estimates for the quarter of the treatment as well as for three leading quarters (*F*=3) considering all treated industry segments and quarters. Detailed results for each estimate are provided in Table 3.6 for deals consummated worldwide, in the United States, and in Europe. However, it is possible that the effect of the first treatment in a given industry segment is different from the effect of the second, third, and fourth treatment in the same industry segment. For example, if a given industry segment received one or more big tech start-up acquisitions in quarters 8, 20, 23, and

37, there may be differences in the behavior of the outcome variables on and after the first (8), second (20), third (23), and fourth (37) treated quarter.

To explore this possibility, we analyzed the effect on and after the very first treated quarter of each treated industry segment. The results are also reported in Table 3.6 for ease comparison with the results of the average effects obtained when all treatment units are considered. The effect on and after the second, third, etc. treated quarters was not explored in detail, although the detected pattern of first quarter and average effects suggests that there is a tapering off.

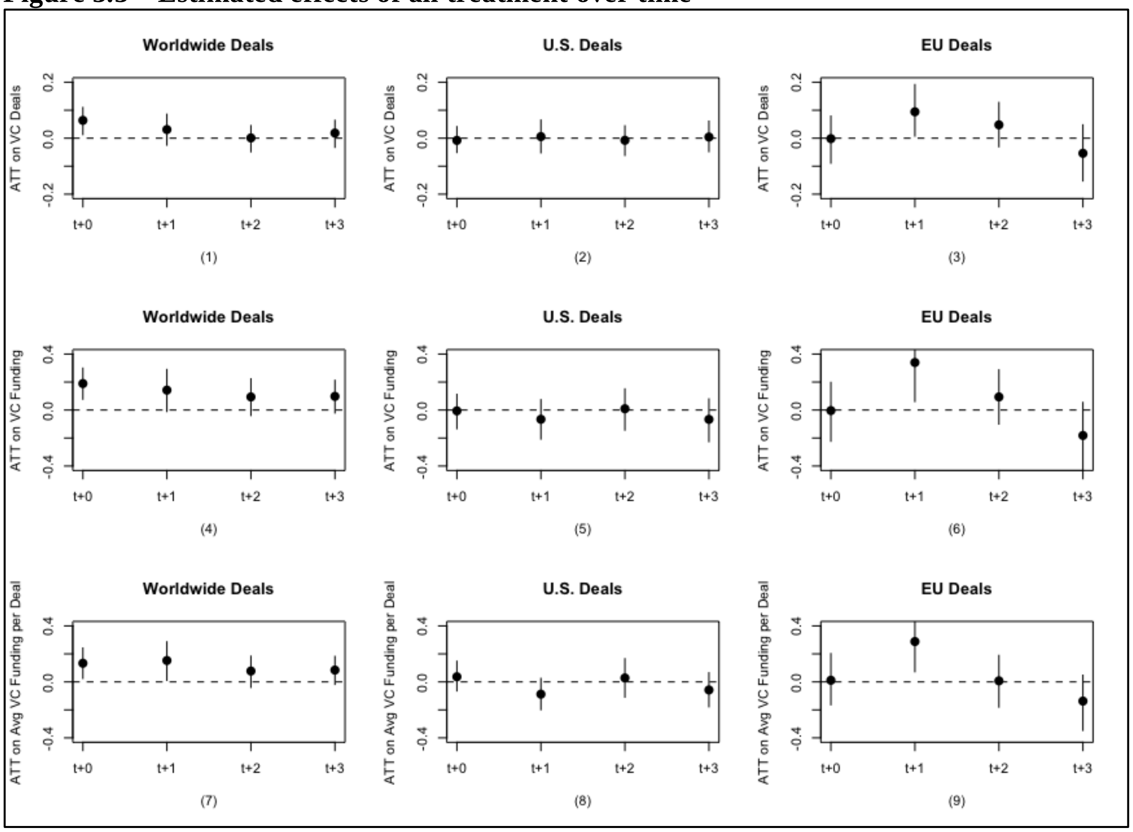
Table 3.6 – Results of DiD inference

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel	Worldwide	U.S.	Europe	Worldwide	U.S.	Europe	Worldwide	U.S.	Europe
Dependent variable	VC Deals	VC Deals	VC Deals	VC Fund	VC Fund	VC Fund	Avg VC Fund	Avg VC Fund	Avg VC Fund
All treatment									
ATT	0.0637**	-0.0078	-0.0016	0.1892**	-0.0058	-0.0038	0.1332**	0.0365	0.0116
	(0.0295)	(0.0298)	(0.0532)	(0.0712)	(0.0758)	(0.1197)	(0.0621)	(0.063)	(0.1083)
ATT 1 quarter post	0.0309	0.0057	0.0944*	0.1422	-0.066	0.3397**	0.1526*	-0.0879	0.2882**
	(0.0338)	(0.0356)	(0.0549)	(0.0915)	(0.0837)	(0.1562)	(0.0848)	(0.0714)	(0.1398)
ATT 2 quarters post	0.001	-0.0075	0.0477	0.0937	0.0092	0.0936	0.0775	0.0281	0.0075
	(0.0297)	(0.0341)	(0.0515)	(0.0772)	(0.0926)	(0.1166)	(0.0677)	(0.0847)	(0.1147)
ATT 3 quarters post	0.0184	0.0042	-0.0539	0.0977	-0.0666	-0.1817	0.0844	-0.0576	-0.1372
	(0.0316)	(0.0336)	(0.0622)	(0.0715)	(0.0914)	(0.1506)	(0.0606)	(0.0749)	(0.1296)
Treated Obs.	257	198	62	257	198	62	257	198	62
Avg. Untreated Obs.	112.2	125.5	150.5	112.2	125.5	150.5	112.2	125.5	150.5
First treatment									
ATT	0.1217**	0.0203	-0.0672	0.1548	-0.0362	-0.2079	0.0034	0.0104	-0.147
	(0.0505)	(0.0565)	(0.0635)	(0.1266)	(0.1579)	(0.1416)	(0.1231)	(0.1272)	(0.1296)
ATT 1 quarter post	0.1788***	0.1402**	0.0529	0.4861***	0.1668	0.2708	0.3158**	0.0611	0.2427
	(0.0489)	(0.0583)	(0.0581)	(0.1479)	(0.1536)	(0.197)	(0.1383)	(0.1394)	(0.1801)
ATT 2 quarters post	0.1163*	-0.0305	0.0181	0.3931**	-0.1115	-0.077	0.2431*	-0.1099	-0.1779
	(0.0622)	(0.0727)	(0.0517)	(0.1614)	(0.2077)	(0.1391)	(0.1332)	(0.1746)	(0.1557)
ATT 3 quarters post	0.0483	0.0144	-0.0906	0.0942	-0.2025	-0.2866	0.0039	-0.1873	-0.2229
	(0.0538)	(0.0729)	(0.0592)	(0.1386)	(0.1843)	(0.173)	(0.118)	(0.1553)	(0.1603)
Treated Obs.	63	58	39	63	58	39	63	58	39
Avg. Untreated Obs.	161	162.6	167.6	161	162.6	167.6	161	162.6	167.6

Outcome variables were log transformed.
Average number of untreated observations included in the matched control set of each treated observation.
Avg VC fund. reports the average amount of funding per VC deal per industry segment per quarter, in millions of U.S. dollars, considering only industry segments and quarters that received at least one VC deal.
Standard errors in parentheses were calculated through a block-bootstrapped procedure with 1,000 iterations. For details, see Imai, Kim, and Wang (2021, p.12).
* p<0.10, ** p<0.05, *** p<0.01

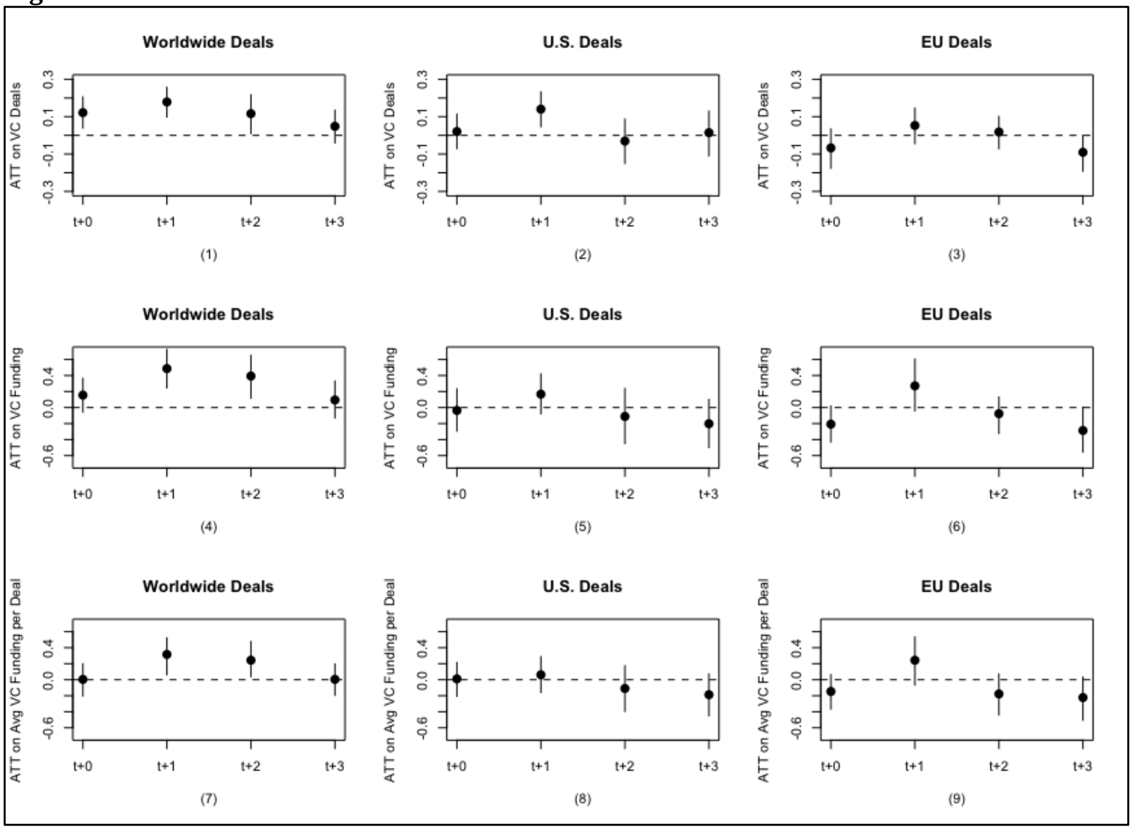
Figures 3.3 and 3.4 provide graphical illustrations of the estimated average effects presented in Table 3.6 and their 90% confidence intervals considering all treatment units, as well as only the very first treatment unit of each industry segment, respectively. The choice of *F=3* was made to preserve coherence with the assumed carry-over effect of three time-periods (*L*=3) detailed in Section 3.6.20. Choosing a larger *F* would complicate the interpretation of the estimated ATTs, because it would increase the chances of treated industry segments receiving another treatment during the *F* lead time periods.

Figure 3.3 – Estimated effects of all treatment over time



90% confidence intervals based on block-bootstrapped standard errors using 1,000 iterations. For details, see Imai, Kim, and Wang (2021, p.12).

Figure 3.4 – Estimated effects of first treatment over time



90% confidence intervals based on block-bootstrapped standard errors using 1,000 iterations. For details, see Imai, Kim, and Wang (2021, p.12).

Using data of deals consummated worldwide, the results presented suggest statistically significant, positive, average effects of big tech start-up acquisitions on the total number of VC deals, total amount of VC funding, and average amount of VC funding per deal in treated industry segments. Higher average effects were found when we considered only the very first quarter of each industry segment that had received one or more treatments. Considering all treatments, an average increase of 6.37% [1.2%, 11.1%][15] on the total number of VC deals was found in the quarter of the treatment. The effects on the first, second, and third quarter after the treatment were not statistically different from zero. However, when we explored the

[15] This and all other percentage values reported in brackets after the coefficients discussed in Section 3.6 refer to 90% confidence intervals.

average effects of the first treatment only, we found a 12.17% [3.96%, 20.57%], a 17.88% [9.81%, 25.68%], and a 11.63% [0.96%, 21.74%] increase in the number of VC deals in the quarter of the treatment and the two quarters following it, respectively.

When we examined the average effects of treatment on the amount of VC funding, we found a 18.92% [7.05%, 29.7%] increase in the quarter of the treatment when we analyzed all the treatments and a 48.61% [24.52%, 72.46%] and 39.31% [11.77%, 65.22%] increase in the two quarters following the quarter of the treatment, when we considered only the very first treated observation of each treated industry segments. These results are consistent with the ones reported in Section 3.5 and broadly support our earlier claim that a big tech start-up acquisition in a given industry segment produces a positive sign to venture capitalists that increases their interest in investing in start-ups of that industry segment. However, our dataset and empirical approach do not allow us to make conclusions about the type of positive sign big tech acquisitions gives to VC investors. An acquisition may signal increased market potential, the attractiveness of investment in complementary innovation activities, or a better prospect for a successful exit strategy in the future, as discussed in Section 3.1.

When we considered all treatment observations, we also found a statistically significant 13.32% [3.1%, 23.2%] and 15.26% [1.7%, 28.9%] increase in the average VC funding per deal per quarter in the quarter of an acquisition and the first quarter after it, respectively. When only the very first treatment was isolated, the average effects found were bigger: a 31.58% [6.2%, 52.23%] and a 24.31% [3.83%, 47.64%] increase, respectively. This shows that, although the average impact of an increment in the number of big tech start-up acquisitions is not statistically different from zero (as reported in Section 3.5), we can observe a statistically significant difference in the average VC funding per deal between treated and untreated industry segments after an acquisition.

An analysis of the effects of big tech acquisitions of U.S.-based start-ups on venture capital activity in the United States found no statistically significant average effects when we considered all treatment observations. As already discussed in the previous section, one explanation for these results may be the existence of highly dynamic venture capital activity in the United States. When only the very first treatment observations per industry segment were considered, a 14.02% [4.64%, 23.27%] average increase in the number of VC deals was found in the first quarter after a big tech acquisition of a U.S.-based start-up.

In contrast, when all treatment observations were considered in Europe, we found a 9.44% [0.5%, 18.1%] and a 33.97% [8.9%, 59,7%] increase in the number of VC deals and amount of VC funding in the first quarter following the quarter of an acquisition, respectively. Furthermore, we also found a statistically significant 28.82% [5.96%, 51.50%] increase in the average amount of VC funding per deal in the first quarter after the treatment. These results align with the results of the two-way fixed effects Poisson estimation reported in Section 3.5. They challenge claims that big tech start-up acquisitions discourage VC investment in other European start-ups. It is interesting that no statistically significant effects were found in Europe when we considered only the very first treatment per industry segment. This suggests that not only the very first treatment, but also the following treatments affect the VC activity.

Finally, after a careful analysis of the results presented in Table 3.6 and illustrated in Figures 3.3 and 3.4, one may argue that mostly insignificant results were found for the United States and Europe, although strong, positive, average effects of big tech start-up acquisitions on VC activity were found using the panel of deals that happened worldwide. This raises questions about which countries and regions could be driving the results found for the worldwide VC activity. One explanation for such results may be the existence of transregional effects of big tech start-up acquisitions on VC activity. Although our analysis for the United States and Europe explored only the effects on their respective VC activity of acquisitions that happened in these regions, it is plausible to expect that big tech acquisitions of start-ups based in the United States, China, or Latin America, for example, also affect VC activity in Europe, and vice-versa. This would contribute to an overall statistically significant effect found when industry segments are analyzed regardless of geographic breakdowns. To support such a claim of the existence of transregional effects of big tech start-up acquisitions, we have investigated the effects of U.S.-based acquisitions on VC activity in Europe. The results, reported in Figure II.4 of Appendix II, confirm the existence of such transregional effects.

Our empirical analysis was based on thousands of venture capital deals, M&As, IPOs, and big tech start-up acquisitions consummated between 2010 and 2020 in more than 170 industry segments of the tech-related economy. It provides robust grounds for rejecting the existence of measurable negative effects of big tech start-up acquisitions on VC activity in these industry segments. Instead, we found statistically significant, positive effects. Our findings also show that when such positive effects exist, they persist primarily for a few months only and thus do not appear to have lasting impacts on the innovation incentives in the start-up ecosystem.

One potential objection to our results is the hypothesis that time-variant, informational shocks (e.g., a technological discovery or a new use-case for a technology) explain the findings. The econometrician does not observe such shocks, but the big techs and VC investors commonly observe them. They spur both acquisitions and VC activity and explain the strong association between big tech acquisitions and VC activity found in our empirical investigation. We believe that this hypothetical scenario is implausible for two reasons. First, it is very unlikely that these informational shocks happen frequently enough to explain the average, positive response of VC activity to big tech start-up acquisitions, especially when one considers that we analyzed 392 big tech start-up acquisitions.

Second, if one reasonably assumes that an M&A transaction (such as a big tech start-up acquisition) is more complex and time consuming than a VC investment, the effects of a common informational shock should first be perceived in the VC activity and then in the level of big tech start-up acquisitions, or simultaneously in the most optimistic scenario. But our empirical findings show that the opposite happens. Indeed, an overall analysis of the results reported in Tables 3.3, 3.4, 3.5, and 3.6 of Sections 3.5 and 3.6 allows us to conclude that that the effects in future VC activity (first to third quarter after the quarter of the acquisition) are bigger in magnitude and statistical significance than the effects in the current VC activity (same quarter of the acquisition). In other words, if the average, positive effect on VC activity found is an average response to common, information shock that also caused big tech start-up acquisitions, the effect on big tech acquisitions should happen later than or even simultaneously to the effect on VC activity and not sooner.

3.7. Implications for Competition Policy and Regulation

Our empirical investigation of the effects of big tech start-up acquisitions revealed nuanced patterns. Overall, we detected evidence of a positive, statistically significant increase in venture investment in the industry segments in which the acquired start-ups operate. During the ten-year period covered in our data, there are no, detectable, systematic negative effects on start-up funding. Thus, the empirical evidence suggests that, in a given industry segment, venture capital resources available to start-ups for innovation purposes increase after big-tech acquisitions. However, our analysis also shows that these effects are transitory and taper off over time. By the same token, our results do not suggest that promoting big tech start-up acquisitions is an instrument to advance lasting start-up innovation. To examine this issue, additional research would be required to investigate the long-term effects on innovation incentives.

These results challenge broad claims about the existence of short-term, negative impacts of big tech acquisitions on innovation, because of the creation of "kill zones" for start-ups. Our findings do not imply that such "kill zones" might not exist in specific cases, but there does not seem to be a systematic pattern across industry segments and extended periods. This should raise a flag of caution for current, competition policy discussions about imposing restrictions on the ability of big techs to acquire start-ups. It is difficult to establish a reliable, general, counterfactual of what might happen if broad competition policy restrictions were put into place.

In this scenario, several effects could happen which cannot be explored with our dataset and empirical approach. It is plausible to expect that VC investors and entrepreneurs would have lower incentives to fund innovation due to diminished expectations of a successful exit of their investment by selling to a big tech (Cabral, 2021). It is also plausible to expect that, once big tech acquisitions are more difficult/rare, the effect of an acquisition on VC activity would be even higher, as it would signal a very strong interest of a big tech on an industry segment. We cannot provide supporting evidence for either of these scenarios, because our data is based on an observation period during which big tech start-up acquisitions were not made more difficult than any other M&A transaction. These ambiguities suggest that a case-by-case approach in which the evidence can be weighed carefully is superior to generic rules.

These findings complement the work by Gautier and Lamesch (2021) as well as by Callander and Matouschek (2021). However, based on our robust empirical findings, we draw more cautious conclusions for the appropriate role of competition policy. We find ourselves more in line with Federico et al. (2020), who propose that competition enforcers analyze in merger reviews, the past acquisitions of the incumbent platform seeking to acquire a nascent start-up, to assess whether the platform has a pattern of terminating acquired innovation projects or integrating them to enhance their products and services.

Big techs' acquisition strategies could have a median, socially positive outcome, because they foster innovation through increased venture capital activity. However, there are potential downsides because the mean effect of these activities may not be positive. This could happen if such acquisitions eliminate a "black swan" competitor, a start-up that might evolve into the "the next big digital platform." Because start-ups are very dependent on a few big techs to succeed, it is plausible to assume that more competition in platform markets, such as social media, app stores, cloud services, etc., should not only bring more innovation to these markets, but also reduce the risk of investing in technology start-ups in other markets. Such a risk-reduction effect would have a positive impact on the entire innovation ecosystem by fostering more start-up creation and VC investment in many niches of the technology industry.

The adoption of regulatory or antitrust safeguards to avoid harm to innovation from big tech acquisitions in the long run is highly controversial. The current consumer standard used in antitrust in the United States often fails to capture such long-run effects. As Erik Hovenkamp emphasized in U.S. Department of Justice (2020), it should not be considered a competition policy issue if it is too hard to compete against the network effects and data analytical capabilities of the big tech companies. Nonetheless, competition policy and regulation should be concerned about the impact of big tech acquisitions on the trajectory of the market. Thus, the evidence needs to be compelling that an acquisition may kill or hinder the emergence of a start-up that might become a next big tech.

Furthermore, while only some start-up acquisitions should be viewed as motivated by a tentative of pre-empting competition for the incumbent platforms, the establishment of objective criteria to decide whether an acquired start-up would have means to challenge an incumbent platform in the long run is very complex. In this context, research literature and policy reports consent on the need for a closer and stricter monitoring of big tech start-up acquisitions by competition policy enforcers (U.K. Treasury, 2019, Gautier and Lamesch, 2021). A detailed review of several alternative measures can be found in Chapter VI of this dissertation.

3.8. Main takeaways

This chapter analyzed conceptually and empirically the effects of start-up acquisitions made by the big techs in the past decade on innovation incentives in different segments of the tech industry. It showed that theoretically, big tech start-up acquisitions can have both positive and negative, short, and long run effects on innovation and consumer welfare. Thus, empirical data will be needed to help discern these effects. The literature review also allowed us to conclude that a closer monitoring of these mergers would be beneficial, and that competition policy enforcers should be better equipped to analyze the complexities of digital markets. Moreover, having reviewed a wide list of possible reforms to the current merger framework proposed by the research literature, we could also conclude that customizable competition policy remedies, possible to be implemented in a case-by-case basis, are generally preferable to blanket prohibitions of mergers in platform markets.

The empirical investigation provides robust grounds for challenging claims about the existence of measurable, short-term, negative effects of big tech acquisitions on venture capital funding for innovation by start-up firms. After controlling for other factors that may affect VC activity, such as IPOs and other M&As, we found a statistically significant increase in the VC activity in response to big tech start-up acquisitions in different geographical breakdowns. The findings show, however, that such positive effects of big tech start-up acquisitions on VC activity persist for a few months only. Thus, they may not have long-term impacts on the innovation incentives in the start-up ecosystem.

Aspects that deserve further investigation are potential spillover effects of big tech start-up acquisitions on industry segments adjacent to those selected by the big techs for the acquisitions. In fact, the observed increase in VC funding in industry segments that received such acquisitions may be a consequence of reallocation of funding from other similar industry segments. Future research should find it relevant to analyze the data of start-up creations and their death rates to investigate whether big techs' start-up acquisitions affect entrepreneurship and founders' willingness to create new start-ups in the same industry segment, as well as their chances for success after a big tech acquisition happens in their industry segment.

CHAPTER IV – MARKET POWER ASSESSMENT IN DIGITAL MARKETS: CONCEPTUAL FRAMEWORK

This chapter examines the conditions under which a need arises to safeguard and promote competition in digital markets. The concentrated structure of several digital markets requires the identification of firms with market power (U.K. Competition and Markets Authority, 2020). However, the methods to assess market power in the context of digital markets are not fully developed and many experts believe that they must be redefined (Scott-Morton at al. 2019). This chapter discusses which digital platforms and markets should be targeted by pro-competitive remedies and proposes a new approach to assess market power in digital markets.

The recent competition policy literature suggests a need to reconceptualize the notion of market power in digital markets, as and of the tools employed to identify whether one or more firms possess such power (Scott-Morton at al., 2019; U.K. Competition and Markets Authority, 2020). For example, the report from the government of United Kingdom (U.K. Treasury, 2019), states:

> A key component of this system is to develop a clear legal test for the characteristics of a company's market position above which regulatory powers are appropriate – termed in this review a strategic market status. This needs to be carefully designed to identify where companies operating platforms are in a position to exercise potentially enduring market power, without granting an excessively broad scope and bringing within the bounds of regulation those companies who are effectively constrained by the competitive market. Only a small number of companies should be within the definition of a well-defined test that matches the characteristics of the sector (U.K. Treasury, 2019. p. 81).

According to U.K. Treasury (2019), it is more complex to identify a firm with market power in a digital market than simply identifying whether it has a high market-share in the provision of a digital service. Market power, or monopoly power, is traditionally defined as "the ability of a firm (or group of firms) to raise and maintain price above the level that would prevail under competition" (OECD, 1993). This definition has been operationalized differently around the world according to countries and markets idiosyncrasies.

U.K. Treasury (2019) as well as the European Commission (2020) suggest that the framework of "significant market power," widely used in the telecommunication regulatory framework, provides a good starting point for defining market power in the digital economy. Indeed, Scott-Morton et al. (2019, p. 80) agree that the "communications sector may offer the best guidance for how to approach public accountability for digital platforms." Furthermore, in the debate about how to identify the market power of digital platforms, these scholars advocate for defining the concept "bottleneck power". They relate bottleneck power to the market position of a digital platform in which it becomes a gatekeeper, able to control the access of its competitors to the consumers.

This concept derives from the definition of firms that serve as competitive bottlenecks. It refers to a characteristic that should be attributed to a platform in which the two sides of the market relate in an asymmetric fashion. Consumers on one side of the market primarily single home, that is, they rely on a single platform. Retailers and advertisers on the other side of the market typically multi-home. They join two or more platforms to get access to potential consumers across all these platforms (Armstrong and Wright, 2007). In this scenario, each platform clearly acts as a gatekeeper controlling who has access to its consumers, because the only way to reach a group of consumers is to interact with the unique platform that serves them.

However, if consumers multi-home or have easy means to do so (as is the case in many digital markets today), even big, digital platforms do not constitute competitive bottlenecks. For example, internet users access a variety of media- streaming platforms every day (e.g., YouTube, Twitch, IGTV, Tiktok, Spotify, etc.) to consume different media contents. Thus, they effectively multi-home. Consequently, although YouTube has a large market share among media-streaming platforms and may hold market power in this digital market, it does not serve as a competitive bottleneck. Retailers and advertisers have other options to reach YouTube users, not only in the media-streaming market but also in other digital markets (e.g., social media, search engines, etc.).

In addition, because platforms offer, in user-sided markets, digital products and services (e.g., social media applications, webmail, and maps) that are easily accessible through the internet, a position in which a dominant platform has “bottleneck power” to block the access of its consumers to other entrant platforms is unlikely. An additional issue for basing economic regulation on the identification of “bottleneck power” is that even platforms popular in only one digital market may hold such a position. Imposing pro-competitive remedies on platforms may harm their ability to compete with bigger platforms that play in several digital markets. For example, in a scenario in which Apple Music and Spotify are both considered to hold “bottleneck power” in the music-streaming market, any resultant competition policy or regulatory remedy applied on both platforms to harm Spotify disproportionally, which has its main source of revenues in this market.

To expand current knowledge and contribute to the definition of policy and regulatory tools to promote competition in digital markets, this chapter proposes a conceptual framework to assess market power of digital platforms. It proposes alternative ways to assess the market power of digital platforms building on discrete choice demand theory. The approach examines the common case where a digital platform has a dominant position in several user-side, digital markets. In a first step, a general utility function of users of digital services is outlined, following the well-known discrete choice demand model setup proposed by Berry (1994). This allows deriving own-demand elasticity functions for digital services. The same approach is used to derive a general utility function and own-demand elasticities of advertisers seeking to purchase ad services from digital platforms, one of the most common supplier-side services provided by digital platforms. Next, functions for the market power of digital platforms are derived from the elasticity functions. Finally, their implications for the definition of relevant markets and the design of competition policy tools and remedies are discussed.

The market power functions found are general in that they are applicable to any two-sided market in which, on the user-side, an intermediate, digital platform supplies digital services (zero-priced or not) bundled with digital ads and data collection procedures. The choice to study the targeted ads market on the supplier side of the platform was made for analytical and practical reasons, because the supply of target ads is a well-known, extremely successful business model exploited by digital platforms. However, the models are applicable to other supplier-side markets without loss of generality.

4.1. Market power conceptual framework

Assume a discrete choice demand setting in which there is a platform $k \in K$ in market $m \in M$ providing one digital service j with quality $q_{k,m}$ to internet user $i \in I$. To use the service j, i is required to pay the price $p_{k,m}$ to access it, to spend the total time $t_{k,m}$ watching digital ads while using j, and to share $d_{k,m}$ amount of information with the platform (e.g., digital traces, demographics, behavioral and psychological characteristics, etc.).[16] In the advertising market $g \in G$, the platform *k* supplies the time gathered from each of its users of m to advertiser $a \in A$ at price $r_{k,m,g}$ per impression.[17]

For example, consider Google selling digital ads to advertisers in the United States and reaching YouTube users in Germany. In this case, market *m* is the video-streaming market in Germany, g is the digital ads market of the United States, *i* is an online video user in Germany, a is an advertiser in the United States, *j* is YouTube, and *k* is Google. Moreover, Google charges $p_{k,m} = 0$ from *i* to access YouTube but inserts $t_{k,m}$ seconds of ads on its videos and collects $d_{k,m}$ amount of digital traces from its users. Also, Google charges $r_{k,m,g}$ from any advertiser in the United States to deliver digital ads through YouTube to its users in Germany.

User-side Utility Model

Internet user *i* derives utility $U_{i,k,m}$ when it consumes *j* provided by *k* in market *m*.[18] Such utility comes from the value of the quality characteristics of *j*, $q_{k,m}$, which are commonly related to aspects, such as the nature of the content (e.g., audiovisual, text), its theme (e.g., sports, communication, news, games, etc.), its source, its length, etc. (Prasad et al., 2003; Fan et al., 2007; Bounie et al., 2017). For simplicity, the value given to quality characteristics of *j* is assumed to be constant among internet users, as considered in previous studies. Although the preferences of i previously collected by platform *k* in *M* may also impact the quality of some

---

[16] Usually, $p_{k,m}$ is zero in ads-sponsored, digital products/services.

[17] Ad prices are typically expressed as cost per thousand or cost "per *mille*." There are many variants for how digital ads are priced (per impression, per action, per transaction, etc.), although this does not affect the analysis carried out in this paper.

[18] Because each platform *k* is assumed to provide one digital service *j*, the subscript *j* is dropped in equation 4.1.

digital services, this depends on how customizable the service is, what information is collected, and the existence of consistent, previous interactions between the user and the platform.

The amount of digital ads bundled with *j*, $t_{k,m}$, is well documented in the literature of online advertisement economics as a source of disutility to digital content consumers (De Corniere and Taylor, 2014). This disutility is dependent on the user's nuisance cost of watching ads, α, generally assumed by the literature to be constant among all internet users after controlling for their personal preferences and socio-economic conditions (Dukes and Gal-Or, 2003; Prasad et al. 2003; Papies at al. 2011; Acquisti and Spiekermann, 2011; Zhang and Sarvary, 2015; Bounie et al., 2017).[19] The homogeneity assumption of α among all internet users and platforms is further discussed and relaxed in the next subsection, where I argue that the size and reach of the platform *k* in digital markets *M* also affect the user's nuisance cost of watching ads experienced by the platform users.

The level of information (length and diversity) collected from *i* while she consumes *j*, $d_{k,m}$, is also considered in the literature a source of disutility, dependent on a nuisance cost of data collection, β, assumed, for now, to be constant among all internet users and platforms. However, evidence was found that internet users generally would not be able to have a sense of this disutility, and therefore it would have no impact on consumption decisions (Tucker, 2012; Strandburg, 2013). However, recent improvements in the transparency of privacy policy among digital platforms and other internet suppliers may have resulted in an increase of the importance of privacy issues among internet users (Martin, 2018; Johnson et al., 2018; Wang and Herrando, 2019). Finally, consumer *i* derives disutility of paying $p_{k,m}$ to access *j*, dependent on her price

[19] Tucker (2012) argues that consumers derive some benefit from being well informed about products that they most likely have interest in purchasing. However, such benefit generally is not sufficient to make positive the total utility they derive from spending time on ads, because they originally want to consume a digital content or service, not an ad.

responsiveness, γ, also assumed, for now, to be constant among all internet users and platforms. The homogeneity assumptions of β and γ are also relaxed in the next subsection.

Equation (4.1) models the overall utility $U_{i,k,m}$, which also includes unobservable factors related to product *j* of platform *k* ($\xi_{k,m}$) that also have an impact on $U_{i,k,m}$, as well as an error term $\varepsilon_{i,k,m}$. Equation (4.2) expresses the mean utility function, which is independent of users' heterogeneity and thus is only a function of the characteristics of the digital service provided by platform *k* in market *m*.

$$U_{i,k,m} = q_{k,m} - \alpha t_{k,m} - \beta d_{k,m} - \gamma p_{k,m} + \xi_{k,m} + \varepsilon_{i,k,m} \tag{4.1}$$

$$\delta_{k,m} = q_{k,m} - \alpha t_{k,m} - \beta d_{k,m} - \gamma p_{k,m} + \xi_{k,m} \tag{4.2}$$

Now let us consider $s_{k,m}$ the market-share of *k* in market *m*. Assuming that $\varepsilon_{i,k,m}$ is identically and independently distributed according to a Type I extreme value distribution, Berry (1994) and Nevo (2000) showed that $s_{k,m}$ can be expressed in the classic *logistic* form as the probability that user *i* consumes *j* provided by *k*, given that she derives the mean utility $\delta_{k,m}$ from this choice.

$$s_{k,m} = \frac{\exp(\delta_{k,m})}{1+\sum_{k=1}^{K}\exp(\delta_{k,m})} = \frac{\exp(q_{k,m}-\alpha t_{k,m}-\beta d_{k,m}-\gamma p_{k,m}+\xi_{k,m})}{1+\sum_{k=1}^{K}\exp(q_{k,m}-\alpha t_{k,m}-\beta d_{k,m}-\gamma p_{k,m}+\xi_{k,m})} \tag{4.3}$$

Writing the market-share of *k* in *m* helps us to derive the own-demand elasticities of internet users with respect to *k*'s level of digital ads, level of information collected, and price, as shown in equations (4.4), (4.5) and (4.6), respectively. The intuition behind the own-demand elasticities is that assuming α, β, and γ are constant among users and platforms, the bigger the market-share of *k* in *m*, the more inelastic is its demand to variations in $t_{k,m}$, $d_{k,m}$, and $p_{k,m}$. Because market-power is usually measured by the Lerner Index as the inverse of own-demand elasticity ($-1/\eta$) (Lerner, 1934), one may easily investigate market power of platform *k* in market *m* by exploring how market-share of *k* respond to variations in the levels of digital ads, information collected, or the access price associated with each of them.

$$\eta_{k,m}(t_{k,m}) = \frac{\partial s_{k,m} t_{k,m}}{\partial t_{k,m} s_{k,m}} = -\alpha t_{k,m}(1 - s_{k,m}) \quad (4.4)$$

$$\eta_{k,m}(d_{k,m}) = \frac{\partial s_{k,m} d_{k,m}}{\partial d_{k,m} s_{k,m}} = -\beta d_{k,m}(1 - s_{k,m}) \quad (4.5)$$

$$\eta_{k,m}(p_{k,m}) = \frac{\partial s_{k,m} p_{k,m}}{\partial p_{k,m} s_{k,m}} = -\gamma p_{k,m}(1 - s_{k,m}) \quad (4.6)$$

Such results reassemble the idea behind the Small but Significant and Non-transitory Increase in Price (SSNIP) test – a conceptual tool used extensively in competition policy and regulation to define a relevant market and assess market power.[20] However, they are extended here to assess market power in markets where the product is zero-priced, which is the case in most digital markets. For such markets, our model suggests that price can be replaced by the level of digital ads, or the extent of information collected and bundled with *j*, because both are also sources of disutility and have an impact on *k*'s market share. For example, equation (4.4) allows us to expect that a platform *k* that has 80% of market-share ($s_{k,m}$) in a user-sided digital

[20] The SSNIP test was first introduced in 1982 by the U.S. Department of Justice Merger Guidelines and has been used also by competition authorities in Europe since the early 1990s. It aims to identify markets in which a hypothetical monopolist can impose profitable increases in price (above competitive levels). Coate and Fisher (2008) provide theory and practical details about the test and its applications.

market m is expected to lose four times fewer users if it doubles the time its users must spend viewing targeted ads, when compared with a smaller platform with only 20% of market-share.

Leveraging market power across user-side, digital markets

So far, the proposed model borrowed from existing advertisement economics literature, which assumes the nuisance costs α, β, and γ are constant among users and platforms, to build a framework for assessing market power of digital platforms in ad-sponsored, two-sided markets. Although the conclusions we have reached still hold when we relax these assumptions,[21] an important result is found when we model nuisance costs dependent on the size and reach of platform *k*. It is plausible to assume that when *i* consumes many other services from a big platform *k* in markets other than m, her wider engagement with *k*, and previous awareness about *k*'s quality standards and functionalities make her switching cost higher than when *k* is a new platform for *i*. Consequently, user *i* would be more tolerant to an increase in the time she needs to spend watching ads in *k* when *k* is a big digital platform, than when k is a small platform. The same rationale also applies to an increase in the level of user information collected by *k*.

As a practical example, this assumption suggests that an internet user who consumes many services from Google, such as Gmail, Google Drive, Google Maps, Google Chrome, and Google Search would accept watching more digital ads on YouTube than on a smaller, unknown platform. Chapter V of this dissertation provides empirical evidence that supports such an assumption. Analyzing online video users' response to ads in an experiment with two

[21] Berry et al. (1995) and Nevo (2000) show that when the heterogeneity of consumers' tastes (their nuisance cost or sensitivity) is considered, own-demand elasticities are still negatively related to the level of prices and the inverse of firms' market-share ($1 - s_{k,m}$), integrated throughout a distribution of consumer tastes.

platforms (a big and a small platform), showed that users are more tolerant to watch digital ads and share information in a big platform, when compared to when they are accessing a small one.

To model such platform heterogeneity and thus analyze its implications for the assessment of the market power, let us consider the nuisance costs α_k, β_k, and γ_k, which are marginal disutilities, now dependent on platform k. To differentiate well-known, multi-market platforms from smaller ones, it the variable $S_{k,-m}$ is used, a function of $n_{k,-m}$ the likely level of engagement of *k* with *i*. First, a platform present in more digital markets is more likely to have a wider engagement with user *i*, who may consume more than one digital service from *k*. As discussed earlier, a wider engagement leads to a higher switching cost, and consequently to a higher tolerance of end users to increased levels of $t_{k,m}$, $d_{k,m}$, and $p_{k,m}$. So, it is expected that the marginal disutilities α_k, β_k, γ_k, and $n_{k,-m}$.

Also, not only being present in many markets, but also having big market-shares in these markets is an important characteristic of *k* to allow one assuming a great engagement between platform *k* and the user *i*. For example, a platform *k* present in several digital markets, and with great market shares in most of them (e.g., Google, Apple, or Amazon) would be more likely to have a wider engagement with consumer *i* than a platform which is present in many digital markets, but with little market shares on all or most of them. To capture such features, the total level of market shares of *k* in all the markets other than *m* where it is present is modeled by the simple sum of all the market shares, $\sum s_{k,-m}$.

Another important factor to consider when modeling the potential level of engagement of *i* with platform *k* is how the market shares of *k* are distributed around the $n_{k,-m}$ digital markets other than *m* where it is present. For example, consider Platform 1 with 80% of market share in market A, 20% in market B, and 50% in market C. Now consider Platform 2 with 75% of market share in market D, and 75% in market E. Now consider that Platforms 1 and 2 compete in another market (e.g., market F), subject to market power assessment by competition authorities. Which platform is more likely to have a wider engagement with consumer *i* of market F, an internet user which, most likely, also consume digital services in all the other markets (A to E)? It is reasonable considering that, even though the total market shares $\sum s_{k,-m}$ of both platforms on markets A to E are equal (in this case, 150%), Platform 1 may be engaged with *i* in three digital services other than *j*, while Platform 2 only in two other digital services. This difference should lead to a higher switching cost (and tolerance to disutilities) of *i* with respect to Platform 1 than to Platform 2 on market F. This characteristic can be captured by a simple interaction between the number of markets where *k* is present other than *m*, and the total market shares of *k* in markets other than *m*, $n_{k,-m}.\sum s_{k,-m}$.

Finally, we assume that the marginal increase of $S_{k,-m}$ as a response of an increase in the interacted term $n_k.\sum s_{k,-m}$ should be decrescent with increases in $n_{k,-m}.\sum s_{k,-m}$. This can be explained by the fact that most internet users are not present or active in all digital markets, as digital services usually compete for the users' online time. Based on this, and in the fact that the level of engagement between *i* and *k* should be a non-negative variable, $S_{k,-m}$ is modeled as the natural logarithm of one plus the product between the number of different digital markets where *k* is present other than *m*, and the sum of *k*'s market-shares in all user-side digital markets other than *m* ($S_{k,-m} = \ln(1 + n_{k,-m}\sum s_{k,-m})$). Equations (4.7), (4.8) and (4.9) provide general forms of the marginal disutilities α_k, β_k, and γ_k dependent on $S_{k,-m}$.

$$\alpha_k = \alpha_0 - \alpha_1 S_{k,-m} = \alpha_0 - \alpha_1 \ln(1 + n_{k,-m}\sum s_{k,-m}) \text{ with } \alpha_k \geq 0 \text{ for } \forall\ S_{k,-m} \tag{4.7}$$

$$\beta_k = \beta_0 - \beta_1 S_{k,-m} = \beta_0 - \beta_1 \ln(1 + n_{k,-m}\sum s_{k,-m}) \text{ with } \beta_k \geq 0 \text{ for } \forall\ S_{k,-m} \tag{4.8}$$

$$\gamma_k = \gamma_0 - \gamma_1 S_{k,-m} = \gamma_0 - \gamma_1 \ln(1 + n_{k,-m}\sum s_{k,-m}) \quad \text{with } \gamma_k \geq 0 \text{ for } \forall\ S_{k,-m} \tag{4.9}$$

The interpretation of the equations above is the following. The disutilities, or nuisance costs experienced by *i* when she has to spend $t_{k,m}$ of her time watching ads, or has to share $d_{k,m}$ of her private information, or has to pay $p_{k,m}$ to access and use *j* in market *m* are lower the bigger the digital platform *k*, as the switching cost (and tolerance) of *i* is assumed to be higher with platforms whose which she is more engaged in other digital markets. This implies that internet users would be more tolerant of spending time watching ads and having their information collected from incumbent digital platforms then from new entrants into market *m*. Consequently, an incumbent platform *k* can sustain profitable levels of $t_{k,m}$, $d_{k,m}$ and $p_{k,m}$ above the competitive equilibrium and proportional to its size and reach in the digital economy. Equations (4.10), (4.11) and (4.12) show how the level of market power $\Omega_{k,m}$ of digital platform *k* in market *m* can be leveraged by the extent of *k*'s presence in other digital markets.

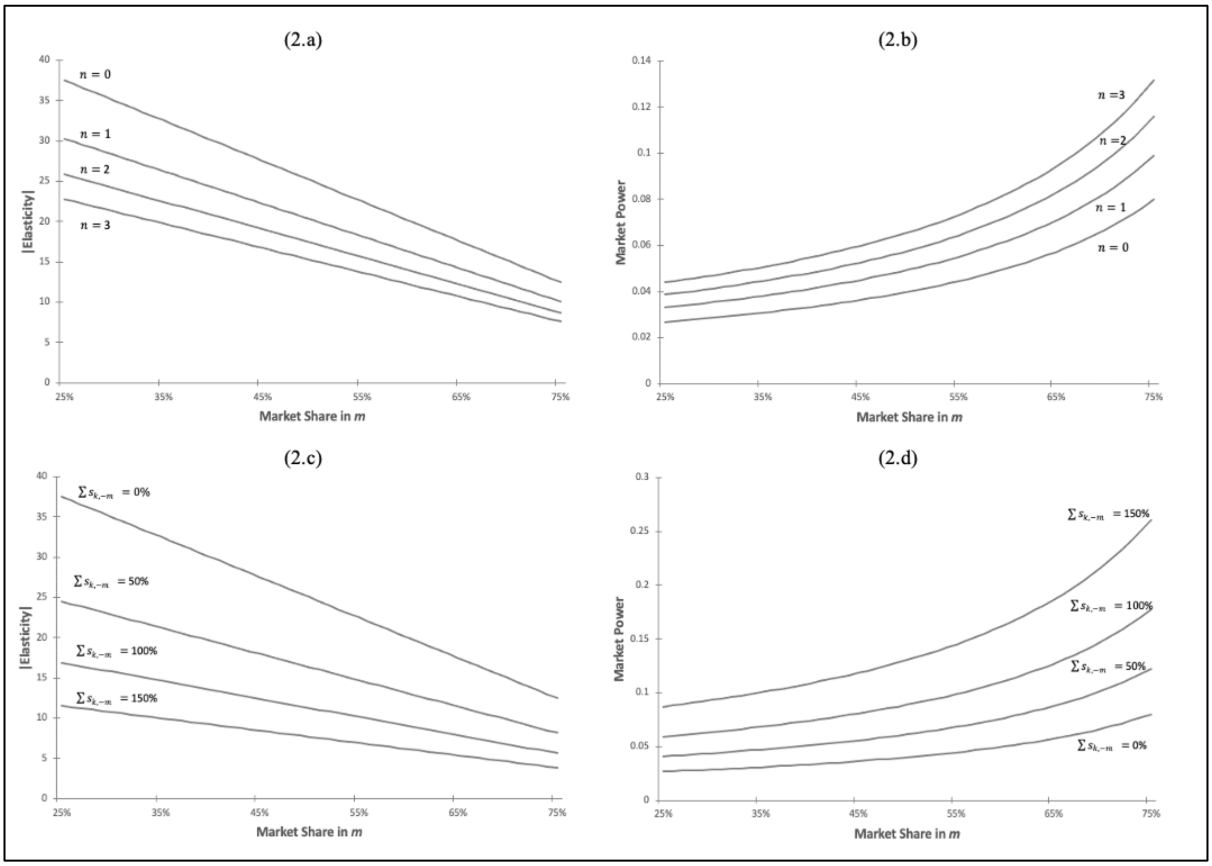
$$\Omega_{k,m}(t_{k,m}) = \frac{-1}{\eta_{k,m}(t_{k,m})} = \frac{1}{[\alpha_0 - \alpha_1 \ln(1+n_{k,-m} \sum s_{k,-m})]\ t_{k,m}(1-s_{k,m})} \tag{4.10}$$

$$\Omega_{k,m}(d_{k,m}) = \frac{-1}{\eta_{k,m}(d_{k,m})} = \frac{1}{[\ln(1+n_{k,-m} \sum s_{k,-m})\ ]d_{k,m}(1-s_{k,m})} \tag{4.11}$$

$$\Omega_{k,m}(p_{k,m}) = \frac{-1}{\eta_{k,m}(p_{k,m})} = \frac{1}{[\gamma_0 - \gamma_1 \ln\ (1+n_{k,-m} \sum s_{k,-m})\ ]p_{k,m}(1-s_{k,m})} \tag{4.12}$$

The equations above allow us to conclude that the greater the presence of platform *k* not only in *m* but also in digital markets other than *m*, the more inelastic is its demand with respect to any increase in $t_{k,m}$, $d_{k,m}$, or $p_{k,m}$, and, thus, the greater its market power is in digital market *m*. Figure 4.1 illustrates such effects, showing that, assuming α_1, β_1 or γ_1 greater than zero, the bigger the number of different digital markets other than *m* where the platform *k* is present ($n_{k,-m}$), and the bigger its total market-share in those markets ($\sum s_{k,-m}$), the lower its own-demand elasticity in *m* and the bigger its market power. Indeed, we can see in the figure that a platform with great presence in other markets but low market-share in *m* may even have a lower own-demand elasticity and a bigger market power in *m* when compared with a platform with a bigger market-share in *m* but without presence in other digital markets.

Figure 4.1 – Elasticity and market power plots in market *m*



Source: Author.

Such results show that the dominant position of an incumbent digital platform in other markets can be leveraged to market *m*, allowing the incumbent platform to sustain higher levels of ads, data collection procedures, and prices when compared with small platforms. A second conclusion is that when a big digital platform is the newcomer in a digital market, instead of competing in terms of the levels of quality, ads, data collection procedures, and price, such a platform may set the same levels chosen by its competitors and still gain a market share.

The implications of such results to set effective, *ex-ante*, regulatory remedies to foster competition in digital markets is further discussed in Section 4.2. However, it is important to note that, if the competition authority wants to analyze simultaneously the market power of a big digital platform in all the user-side markets where *k* is present, a general equilibria approach would be preferable. The market models derived in this Section apply for analyzing market power in just one digital market *m* at once, what is generally acceptable, as this is the most common practice in competition policy and regulation procedures.

Advertiser-side Utility Model

Advertisers, framed herein as buyers in the supplier side of the intermediation platform *k*, derive utility from purchasing digital ads and having their products and services efficiently exposed to the platform users most likely to pay for them. Such utility is a function of the visibility of the advertisement minus the price the advertiser pays for it (Bonnie et al., 2017). Consider the advertising market $g \in G$, where the platform *k* supplies a unit fraction of the time $t_{k,m}$ of *i* to advertiser *a* at price $r_{k,m,g}$. The utility of advertiser *a* can be modeled as a function of the quality of the digital ad offered by platform *k* in market *m* ($\sigma_{k,m}$), and the price that the platform *k* charges in geographic market *g* to show the ad of *a* to user *i* in market *m* ($r_{k,m,g}$).

The quality of the digital ad referred here ($\sigma_{k,m}$) is not related to the content characteristics of the ad, as the ad is generally provided by the advertiser itself to be distributed by the platform. Rather, it is related to the ability of platform *k* effectively targeting the ad towards potential consumers of *a* in market *m*. In this sense, $\sigma_{k,m}$ might be dependent, among others, on the market share of platform *k* in *m* ($s_{k,m}$), as the greater the universe of users of platform *k* in market *m*, the greater the chances of the platform finding relevant consumers for the products and services that *a* seeks to advertise. Moreover, $\sigma_{k,m}$ might be also dependent on the amount and diversity of information that platform *k* collects from its users in market *m* and in all other user-sided markets where *k* is present ($D_k = d_{k,m} + d_{k,-m}$). In fact, a platform with more data of its end users might achieve better accuracy predicting potential customers of *a*'s products and services.

It is important to also note that, intuitively, $r_{k,m,g}$ would depend on $\sigma_{k,m}$, because high quality digital ads may have high production costs. However, because the platform business model creates high economies of scale and scope for the intermediary platforms (Crémer et al. (2019), we assume here that $r_{k,m,g}$ is exogenously defined by the platform according to the level of competition it faces in the ads market g. $U_{a,g,k,m}\xi_{k,m}U_{a,g,k,m}\varepsilon_{a,g,k,m}$

$$U_{a,g,k,m} = \sigma_{k,m} - \phi r_{k,m,g} + \xi_{k,m} + \varepsilon_{a,g,k,m} \tag{4.13}$$

$$\sigma_{k,m} = \theta_0 + \theta_1 D_k + \theta_2 s_{k,m} \tag{4.14}$$

$$U_{a,g,k,m} = \theta_0 + \theta_1 D_k + \theta_2 s_{k,m} + \xi_{k,m} - \phi r_{k,m,g} + \varepsilon_{a,g,k,m} \tag{4.15}$$

Like the scenario described in the previous Subsection, let us consider $s_{k,g}$ the market-share of platform *k* in market g. As shown by Berry (1994) and Nevo (2000) for discrete-choice demand models, assuming that $\varepsilon_{a,g,k,m}$ is identically and independently distributed according to a Type I extreme value distribution, $s_{k,g}$ can be expressed in its classic logit form of equation (4.16), which represents the probability that advertiser *a* chooses ads from *k* knowing the average utility derived from the ads provided by k. It is important to note that a discrete-choice demand setting like this one has certain limitations to model the behavior of advertisers, as several of them multi-home to reach more group of users in different platforms. On the other hand, given the current concentrated structure of many user-side, digital markets, and the rising costs of digital ads campaigns, most publishers and advertisers may opt to advertise in one, wide-reaching platform instead of multi-homing (Loeb, 2021; Johnson, 2022).

Equations (4.17), (4.18), (4.19) and (4.20) provide the derived, own-demand elasticities of *a* with respect to the level of information D_k that platform *k* collects from its users in markets M, as well as to its user-side market-share $s_{k,m}$ and price $r_{k,m,g}$.

$$s_{k,g} = \frac{\exp\left(\theta_0+\theta_1 D_k+\theta_2 s_{k,m}-\phi r_{k,m,g}+\xi_{k,m}\right)}{1+\sum_{k=1}^{K}\exp\left(\theta_0+\theta_1 D_k+\theta_2 s_{k,m}-\phi r_{k,m,g}+\xi_{k,m}\right)} \tag{4.16}$$

$$\eta_{k,g}(D_k) = \frac{\partial s_{k,g} D_k}{\partial D_k s_{k,g}} = D_k\left(1-s_{k,g}\right)[\theta_1 - \theta_2 \beta s_{k,m}(1-s_{k,m})] \tag{4.17}$$

$$\eta_{k,g}(D_k) = \frac{\partial s_{k,g} D_k}{\partial D_k s_{k,g}} = D_k\left(1-s_{k,g}\right)[\theta_1 - \theta_2(\beta_0 - \beta_1 S_{k,-m}) s_{k,m}(1-s_{k,m})] \tag{4.18}$$

$$\eta_{k,g}\left(s_{k,m}\right) = \frac{\partial s_{k,g} s_{k,m}}{\partial s_{k,m} s_{k,g}} = \theta_2 s_{k,m}(1-s_{k,g})] \tag{4.19}$$

$$\eta_{k,g}\left(r_{k,m,g}\right) = \frac{\partial s_{k,g} r_{k,m,g}}{\partial r_{k,m,g} s_{k,g}} = -\phi r_{k,m,g}(1-s_{k,g})] \tag{4.20}$$

The derived own-demand elasticity functions presented in equations (4.17), (4.19), and (4.20) provide important insights for the identification of platforms with market power in the market of advertisement. Equation (4.17) shows us that the higher the market-share of a platform among users of market *m*, the more inelastic is its demand among advertisers of market *g* with respect to a decrease in the level of information D_k that *k* has from its internet users. Similar, and more important, the larger *k*'s market-share is among advertisers on market *g*, the more inelastic is its demand for decreases in D_k and the larger its market power among advertisers. These results suggest that asymmetric measures aimed at reducing the market power of digital platforms on the ads market should also focus on reducing concentration in market m, because the high market-share of the platform in that user-side market plays a key role in lowering its own-demand elasticity in market g.

Furthermore, when we allow β to vary across platforms (see equation 4.18, where I plugged equation 4.8 to equation 4.17), such asymmetric measures should address reducing the market power of platform k not only in the user-side market m but in all user-side markets where k is dominant. Moreover, equations (4.19) and (4.20) show that the larger k's market-share among advertisers of market g, the more inelastic its demand with respect to variations in the price $r_{k,m,g}$ or in the level of market-share k holds among internet users of m. Hence, an approach like the SSNIP test could also be applied by competition authorities in the ads market to identify platforms with market power. Indeed, one could assess the impact on the demand for digital ads of platform k in response to a small but significant non-transitory increase in the level of information that the platform has from its users, or the amount of market-share it has on m, or even in the price of the digital ads offered by k in market g.

The implications of these results for setting effective ex-ante regulatory remedies to promote competition in the supply of digital ads are further discussed in the next Section.

4.2. Guidelines for applying the SMP framework in digital markets

A controversy has arisen about whether traditional t *ex-ante* remedies, introduced in public utility style regulation of the telecommunications sector, should be used to deal with highly innovative, dynamic, and interrelated digital markets dominated by few big digital platforms. Because of these historical roots, I briefly review the most widely used market power framework used in competition policy worldwide, namely the Significant Market Power (SMP) framework.[22] According to the SMP framework, a firm has market power if "it enjoys a position equivalent to dominance, that is to say a position of economic strength affording it the power to behave to an appreciable extent independently of competitors, customers and consumers" (European Commission, 2018a, p. 7).

Furthermore, the European Commission recognizes that, although market share represents a useful first indication of market power, it does not suffice to establish that a firm is in a dominant position. Instead, the Commission considers that the identification of market power also requires a thorough assessment of the firm's ability to impose constraints on its competitors in the medium term. This suggests that market dynamics matter and that a forward-looking approach is needed to assess the firm's ability to sustain its market share. The guidelines of the European Commission suggest non-exhaustive criteria to identify SMP, and several countries inside and outside the European Union have adopted them. They include the existence of barriers to entry, control of infrastructure not easily duplicated, ease or privileged access to capital, vertical integration, presence of high economies of scale and scope in service provision, among others.

According to the same guidelines, to assess whether a firm possesses market power, it is fundamental to start by clearly defining a relevant retail market where such conditions will be analyzed. Once the relevant retail market has been defined, the existence of market power is verified using the already mentioned criteria. If market power is identified, the need to apply regulatory remedies to its upstream wholesale market is analyzed to guarantee fair access to wholesale inputs for all players competing in the retail market. According to the guidelines, to

[22] The most influential reference of this market power framework is the guidelines of the European Commission to telecommunications market analysis and assessment of SMP, firstly released in 2002 and updated in 2018 (European Commission, 2018a). The use of this framework for market power assessment is also recommended by the United Nations' specialized agency for harmonization of digital policy and regulation (ITU, 2016).

define a relevant market, two analyses should be conducted: an analysis of the geographic dimension of the relevant market, and an analysis of the product dimension of the market. These dimensions help delineate the boundaries of the relevant market in which the existence of a firm with market power is assessed.

The geographic dimension comprises an area where the conditions of competition are sufficiently homogeneous and can be distinguished from neighboring areas (European Commission, 2018a, p. 8). Areas in which the conditions of competition are heterogeneous do not constitute a uniform market. Based on such criteria, geographic dimensions have been set ranging from the limits of a city to an entire state or country, dependent on the characteristics of the product and the market structure.

The product dimension comprises

> (…) "all products or services that are sufficiently interchangeable or substitutable, not only in terms of their objective characteristics, their prices, or their intended use, but also in terms of the conditions of competition and/or the structure of supply and demand in the market in question. Products or services that are only interchangeable to a small or relative degree do not form part of the same market" (European Commission, 2018a. p. 6).

The product dimension is analyzed by defining the retail product and investigating the existence of demand-side substitutability and supply-side substitutability. Demand-side substitutability refers to "the extent to which customers are prepared to substitute other services or products for the service or product in question," whereas supply-side substitutability "indicates whether suppliers other than those offering the product or service in question would switch their line of production in the immediate-to-short term or offer the relevant products or services without incurring significant additional costs" (European Commission, 2018a, p. 5). The lack of substitutability on both sides delineates the boundaries of the relevant market.

A practical and widely adopted test of demand-side and supply-side substitutability is the application of the Small but Significant and Non-transitory Increase in Price (SSNIP) test, a traditional tool for market definition in competition policy and regulation. The test basically measures the response of consumers and suppliers to a small but significant and non-transitory increase in the price of a given product or service, assuming that the prices of all other products or services will remain constant. The results help to determine whether substitutable products exist, and where the boundaries of the relevant product market should be delineated.

Considering the conceptual, market power framework proposed in Section 4.1, the following section analyzes the applicability and effectiveness of the SMP framework to assess the state of competition in digital markets dominated by multi-market, digital platforms is analyzed separately for user-side, and for supplier-side markets.

Applying the SMP framework in user-side, digital markets

The assessment of relevant product substitutability in user-side, digital markets is the first step in setting the boundaries of a relevant product market. It is relatively straightforward. For example, there are social media services provided for general purposes (e.g., Instagram) as well as for specific purposes (e.g., LinkedIn). While they might be considered product differentiation in the same, relevant product market, it is clear that other services, such as video-streaming, webmail, etc., do not serve the same purpose or substitute social media services. At this point it is important to recognize that all these services compete for the internet user's attention, a limited resource that also is required to consume off-line, traditional services like attending a music concert or watching a movie in a cinema. The simple fact that two services or products may compete for the user's preference and time does not make them substitutable, and part of the same relevant product market.

Limits to supply-side substitutability are not as easy to delineate as product substitutability. The technology infrastructure built by suppliers of digital services, such as video-streaming and webmail, are costly. Yet, a large, digital platform that is not yet exploring one of these markets can take advantage of its already installed huge technology-intense infrastructure, and big user-base, to launch a service quickly and successfully in a new, relevant product market. Recent examples are Apple's launch of its music and video-streaming services (Apple Music and Apple TV+), or Amazon's launch of its video-streaming platform under its Prime service. However, apart from a few big technology corporations, the quick launch of a large-scale digital service able to compete against those provided by incumbent digital platforms is very difficult for most companies.

Furthermore, it would be straightforward to apply the traditional SSNIP test to define market boundaries in digital markets in cases where monetary payments are required to access and use a service. For example, the user's response to a small but significant and non-transitory increase in the price of a Netflix subscription can be measured, and the market power of Netflix can be compared with the market power of other video streaming services using the framework proposed in Section 4.1 (see equation 4.12). However, when the digital service is accessed and used by the end user free of a monetary charge, a modified approach to the SSNIP test is required. Scott-Morton et al. (2019, p.66) suggest the use of a quality-adjusted price for each service, when the price to access the service is set zero. For those authors, quality could be related, e.g., to the level of utility derived by internet users from the use of the service.

In line with this idea, and informed by the arguments developed in Section 4.1, two additional tests could be used, to assess the response of end users to a small but significant, non-transitory increase in typical sources of disutility rather than changes in price. Such sources of disutility include the level of targeted ads bundled with the service, and the amount of personal data collected by the platform from the user during consumption of the service (effectively a "SSNIA" and a "SSNID" test, respectively, where A accounts for targeted ads and D for data collection). Such tests could be operationalized like the traditional SSNIP test, and their expected results should be governed by the own-demand elasticity functions derived in Section 4.1 (see equations 4.10 and 4.11).

The relevant geographic market dimension could be set pragmatically as the area comprising the jurisdiction of a regulatory authority (e.g., the boundaries of a country or state). Such an approach has been widely used in antitrust cases in Europe when the litigation involves services provided by big digital platforms. For example, one can refer to the German competition authority Bundeskartellamt review of Facebook's potential, anticompetitive conduct in the relevant market of social media (Bundeskartellamt, 2019), as well as the European Commission's review of alleged, competitive misconduct by Google Shopping (European Commission, 2017).

Once a relevant market has been defined, the next step is to identify whether a firm with in such a relevant market has market power. For this, the traditional criteria provided in the beginning of this Section still apply. In addition to an easy analysis of market-share among the internet,[23] most of the big tech platforms have accumulated enormous, sunk assets related to technological infrastructure to provide digital services for millions of internet users. Moreover, they are

[23] The EU guideline established that under 40% of market-share dominance is unlikely; between 40% and 50% of market-share, there is risk of dominance; and above 50% of market-share, dominance is presumed (European Commission, 2018b).

benefited by strong supply- and demand-side network effects (positive externalities), derived from their size and multimarket presence (Crémer et al., 2019). They also have economies of scope and scale to differentiate their services or to bundle them with new ones, and they have easy access to capital.

However, as already introduced in Section 4.1, pro-competitive, regulatory remedies to tackle market power of a big tech in one specific relevant, user-side digital market may not constitute strong enough incentives for other players to enter a market when the incumbent platform is present in several other markets, as is a common scenario in the digital economy. As suggested by the general own-demand elasticity functions derived in Section 4.1 (see equations 4.10, 4.11 and 4.12), multi-market platforms leverage their market power across different digital markets. For example, they experience a more inelastic demand with respect to the level of digital ads, data collection, and price of their products than single-market platforms. In other words, the fact that these platforms provide many different services to internet users makes the users less likely to switch to services provided by entrant firms, even when they provide a superior quality, bundle fewer digital ads, or collect less personal information from their users.

Moreover, Scott-Morton et al. (2019) argue that platform consumers have bounded rationality. For example, consumers are most likely to use the default apps pre-installed in their smartphones and access only the first search results they are shown. Moreover, they incautiously agree with terms and conditions that allow platforms to collect, process, and extensively use their personal information. According to the same authors, consumers make these non-rational decisions because of inherent behavioral biases, such as discounting the future too much and being too optimistic. Such behavioral attributes of internet users aid in diminishing the efficacy of any pro-competitive regulation in one specific digital market.

For example, a user of a social media service provided by a dominant digital platform that also provides other digital services to its users, e.g., payment services, e-commerce solutions, and digital or text-messaging services, might experience significant costs when switching to a new social media provider. This effect might be mitigated if this new provider was another big player that also offers many other services to the user. In another example, an incumbent platform, such as Google, which has large market-shares in many digital markets, might experience a more inelastic demand for its video-streaming service (YouTube) when compared with its competitors (this is explored empirically in Chapter V). Therefore, it should be able to keep its level of market-share stable even when it is identified as with market power and subjected to remedies like interoperability, data portability, and data sharing mandates, aimed at diminishing users' switching costs, and competitors' entry barriers.

In this example, users that are really used to access YouTube to watch videos, and to use several other Google services like webmail, web browser, search engine, maps, cloud, etc., would be less likely to switch from YouTube to a smaller video streaming platform in which they have no previous experience. Thus, Google may charge more for the service, include more digital ads, and/or collect more data from the users than a competing platform without seeing its users' switching to a competitor at the same rate that the competitor would see if adopt a similar strategy.

Therefore, to tackle the market power of big digital platforms and foster competition in user-side, digital markets of the platform economy, a multi-market, coordinated analysis is needed. First, the definition of the relevant digital market should use new tools in addition to the SSNIP test, as the SSNIA and the SSNID tests proposed earlier in this Section. Second, an empirical investigation of platforms with SMP in the relevant digital market should be performed considering the market position of the players in other digital markets as well, as proposed by the framework introduced in Section 4.1 (see equations 4.10, 4.11, and 4.12). Then, pro-competitive remedies should be applied to target a digital platform in all markets where it is present.

Such an approach would be a first step in neutralizing the advantages of incumbent big techs to acquire market share even without offering better services when compared with their competitors. For example, this approach would allow competitors to benefit from information collected by the incumbent platform not just in one market but in all markets where the platform is present. Non-discrimination across markets may also be better guaranteed under this approach. For example, Google should be prevented from discriminating against a competitor of YouTube in Google Search.

Applying the SMP framework in advertiser-side, digital markets

A set of products can be identified in relevant markets of digital ads. It is possible to establish the limits to demand-side and supply-side substitutability with respect to them. For example, for demand-side substitutability, advertisement products that cannot be customized to target a specific audience of interest or have no means to be delivered to it can be defined as beyond the boundaries of the relevant product market. Also, there are different formats of digital ads possible for purchase to reach a given audience. They include a banner in a website, a post on a user's timeline, or a short video to be watched before or in the middle of an online video. They can be considered as product differentiation inside the same market in which slots of digital ads are sold for a non-zero price by competing platforms that reach the same, well-defined audience of internet users.

The definition of limits to supply-side substitutability is even more straightforward. This is because few digital platforms have a huge presence in user-side markets to quickly launch a digital-ads service to offer in advertiser-side markets. Thus, a group of firms can be defined in such a way that no other would be able to provide digital ads to a given, geographically defined audience, because of a lack of information about that audience of internet users, or because there are no means to deliver the ads due to lack of offer of digital services consumed by that audience.

To define a relevant product market, the traditional SSNIP test would be perfectly applicable in digital advertiser markets, given that the product in this case usually is supplied in exchange for a monetary payment. For example, one could analyze the demand response for a small but significant and non-transitory increase in the price of a given digital ads service, such as Google AdSense or Facebook Ads Manager. Furthermore, it is important to consider that digital ads services are not only differentiated by price, but also by the level of customization allowed (a function of the level of data collected by the platform from its users in all user-side, digital markets where the platform is present), and by the size of the audience of internet users possible to be reached by the platform (a function of the platform position in the user-side, digital market of interest to advertiser). Therefore, modified versions of the SSNIP test, which account for factors that have an impact on the demand for digital ads other than price should be used.

Informed by the digital-ads, own-demand elasticity functions derived and discussed at the end of Section 4.1 (see equations 4.18 and 4.19), one should design tests that analyze the response of advertisers and publishers to a small, but significant, non-transitory decrease in the amount and variety of users' data owned by the digital ads supplying platform, or in its market-share in user-side, digital markets (a SSNDD and a SSNDM test, respectively, where DD denotes a decrease in data collected and DM denotes a decrease in market-share in user-side digital markets).

A geographic dimension can also be set for advertiser-side, digital markets. For example, one that comprises advertisers located in the jurisdiction of a concerned regulatory authority. In fact, the aim of any regulatory authority in charge of promoting competition in the supply of digital ads would be increasing the options of digital ads suppliers available to the advertisers and publishers under its jurisdiction. The advertisers, as well as the countless number of brick-and-mortar firms of a given geographic-delimited area that hire advertisers to run their digital marketing campaigns, are the customers in these digital markets seeking for more competition.

The next step would be to identify a firm with market power in such advertiser-side, relevant markets. For this, the criteria provided in the beginning of this Section still apply. The assessment should consider the market-shares of the digital ads supplying platforms not only in the relevant market of analysis, but also in several user-side, digital markets in which these platforms are present. For example, a digital platform with a big market share in each relevant market of digital ads experiences strong network effects from its network size on the other side of the platform, where it gathers the personal data and attention of internet users through the provision of retail digital services. It also derives economies of scope to offer a widely customizable, digital ads service, because of the great amount of data it owns and its strong capacity to generate information from it using costly, technological infrastructure accumulated throughout the years.

Nevertheless, it is important to note that pro-competitive remedies would be unlikely to have significant impact in promoting competition against an incumbent platform in advertiser-side, digital ads markets if it were not enforced jointly with remedies to lower the platform dominance in user-side, digital markets as well. For example, if a competitive entrant had been granted access to the same level of personal information of internet users typically owned by the biggest digital ads supplying platforms, that entrant would be unable to deliver digital ads to a comparable universe of internet users. The entrant would need to be strongly presented in the user-side, digital markets as well. In a comparable way, an entrant platform with access granted to deliver digital ads to a large base of users, but with no or limited information from them, would be unable to compete effectively with incumbent digital platforms in advertiser-side markets, regardless of their price, because of its limitations to offer a highly customizable ads platform.

Therefore, to foster competition in digital ads markets, efforts are required to diminish the market power of incumbent, digital platforms in both user-side and advertiser-side markets. First, the SMP regulatory framework should be adopted, with the definition of all relevant digital markets using tools like the SSNIP test and its variations, the SSNDD, and the SSNDM tests. Then, pro-competitive remedies should be applied to target incumbent platforms in all user-side and advertiser-side relevant markets where they are present.

Such an approach might focus on granting the means to entrant platforms offering a highly customizable digital ads platform for a competitive price, through which advertisers might reach a large audience comparable to the one reached through incumbent platforms. This would compensate the advantages that the current incumbent platforms have, which are derived from the enormous amount of data collected from their immense bases of internet users in several user-side, digital markets.

4.3. Main takeaways

In the era of digital platforms, several policymakers and experts are concerned with the challenge of ensuring that consumers continue to derive benefits from the digital economy. Concerned governmental bodies and scholars around the world have been debating alternatives to foster competition in digital markets and avoid the exercise of market power by almost omnipresent, digital platforms. A review of traditional, competition policy tools and the creation of a regulatory regime over digital markets have been proposed by many stakeholders. However, in either approach, the procedures for market definition, and the identification of firms with market power in digital markets remain highly contested.

In this chapter, it was proposed a conceptual framework for the assessment of market power in digital markets. The proposed economic modeling shows that platforms benefit from multi-market presence, as this makes their end users less likely to switch to smaller competitors even when those offer better services. Considering this characteristic of digital markets, it is discussed the applicability of the traditional Significant Market Power framework to market definition, market power assessment, and to the design of pro-competitive remedies in the context of digital markets. When applied with some adaptations, it is argued that the SMP framework remains relevant to the examination of user-side, and supplier-side digital markets.

In user-side markets, the traditional SSNIP test should be applied to digital services that require a monetary payment for access. However, when the digital service or product is offered free of charge - a common scenario in digital markets - modified versions of this test should be used to analyze the response of the users to small, but significant, non-transitory increases in i) the level of digital ads bundled with digital services (SSNIA test), and in ii) the amount of personal data collected from the users (SSNID test).

Moreover, market-specific, pro-competitive remedies may not assure enough incentives to entry digital markets. Incumbent platforms that are present in several digital markets experience a more inelastic demand with respect to variations in the level of digital ads, data collection, and price of their digital services. To capture these characteristics of platform markets with large players, a multi-market, coordinated analysis is needed. Big digital platforms will have to be targeted by pro-competitive remedies in all markets in which they are present at once.

For supplier-side markets, a special focus is given on the market of digital advertisement, although the results are generalizable to other supplier-side markets. The analyses showed that the SSNIP test applies, but that other tests are also needed to assess the response of advertisers and publishers to a small, but significant non-transitory decrease i) in the amount and variety of internet users' data owned by the supplying platform (SSNDD test), and ii) in the platform's market-share in user-side, digital markets (SSNDM test). However, it is argued that *ex-ante*, regulatory remedies would be unlikely to have significant impact in promoting competition in digital ads markets if they are not enforced jointly with remedies to lower platforms dominance in user-side digital markets.

CHAPTER V – MARKET POWER ASSESSMENT IN DIGITAL MARKETS: AN EMPIRICAL STRATEGY

Recent competition policy research suggests a need to reconceptualize the tools used to identify market power in digital markets (Scott Morton at al., 2019). Chapter IV proposed a conceptual framework for the assessment of market power, aimed at informing policy decisions as to which digital platforms and markets require pro-competitive remedies. A critical point of that framework is whether the disutility of users associated with ads and their privacy concerns vary between incumbent platforms and new platforms (see equations 4.7 and 4.8).

This chapter reports the design and findings of an empirical investigation of the assumption that internet user's nuisance costs due to ads and collection of personal data, and consequently the market power of a platform in one digital market are also a function of its presence and shares in other digital markets. The study analyzes responses of internet users to different levels of advertising and different data collection strategies employed by platforms in the online video market. The research combines an experimental design and survey methods to investigate whether internet users tolerate higher levels of digital ads and data collection procedures in online video services when they are provided by well-known, big digital platforms, rather than by smaller platforms.

This question is of special relevance in digital markets where revenues are heavily dependent on sales of digital ads, made viable by data-driven algorithms, as in the online video market. The existence of such a relationship between the size and reach of the platform and its users' tolerance to ads or data collection could generate a sub-optimal market outcome. Incumbent platforms would show more ads and collect more information from their users than under higher competitive pressure.

The analyses of the results show that the size and reach of the platform, as well as users' prior engagement with other digital services provided by the platform, impact users' tolerance for watching ads and sharing information. This suggests that multi-market, incumbent platforms enjoy a competitive advantage that is exogenous to the relevant market under analysis. The information collected through the experiment was analyzed statistically, and the results suggest that the nuisance cost experienced by Internet users that watch ads bundled with videos accessed through well-known, incumbent video streaming services is lower than that experienced on new platforms. The results also show that the level of ad avoidance of users of online video services is inversely related to the number of services the Internet users consume from the same platform (e.g., webmail, web browsing, search, cloud services, etc.).

Findings from the analysis and experiment contribute to the current debate on methodologies to objectively measure the market power of digital platforms that do not charge a price from users. Chapter IV of this dissertation showed that, when the users' nuisance costs of watching ads depend on the level of their engagement with the platform in other digital markets, a relationship suggested by the results of this experiment, the assessment of market power should consider the platform position in all markets where the platform is present. Also, the results shed additional light on the mechanisms through which big digital platforms can leverage their market power across several digital markets, as well as help informing the debate on how to assess market power in the digital economy and which sort of regulatory remedies could be effective to foster competition.

The rest of this chapter is organized as follows. Section 5.1 reviews the literature on measuring the effects of digital ads and data collection procedures on the enjoyment level of users of online services. Building on this literature, an empirical strategy is proposed to identify variances in users' nuisance cost to digital ads and data collection procedures with respect to the size of the online video platform. Section 5.2 details the experimental strategy used to obtain relevant data for this investigation, outlines the survey instrument used, and the data set gathered. Section 5.3 details the estimation models, and Section 5.4 presents the main results. Section 5.5 discusses the findings, the limitations of this research, and main takeaways.

5.1 Measuring the nuisance costs of digital ads and data collection procedures

Inserting advertisements into media content is a well-known revenue-generation strategy that has been used by traditional newspapers and TV broadcasters for decades. In these traditional media outlets, users of a geographic region are indiscriminately targeted by the same ads, which are a predictable part of the content to be consumed (Logan, 2013). According to the same author, on digital services users are more concerned about having to spend their time watching ads due to an expectation of consuming only the content of interest. The research on the economics of online advertising shows that digital ads inserted in video streaming services, like YouTube, are a source of disutility for consumers (Acquisti and Spiekermann, 2011; Zhang and Sarvary, 2015).

Frade et al. (2021) provide a comprehensive review of studies that identify effects of digital ads on media consumers. Among other results, the reviewed studies show a clear negative impact of in-stream ads on a user's utility from consuming online video services. Such effects are found to vary according to several ad-related factors, like format (e.g., in-stream, banner, etc.), size, duration, position (e.g., at the beginning or at the middle of a video), level of congruence with the main content, etc. These negative effects also depend on user-related factors, like the level of previous engagement of the user with the service, gender, users' content preferences, her country and cultural background, age, etc. (Joa et. al, 2018; Duffett et al., 2019). In contrast, the research literature thus far has typically assumed that the effects of in-stream, digital ads are constant with respect to the characteristics of the digital service provider (Papies at al. 2011; Bounie et al., 2017).

To quantify the tolerance of media users to digital ads, several studies have relied on the scales measuring user ad avoidance proposed by Cho and Cheon (2004). Based on previous studies reported by Vakratsas and Ambler (1999), these authors assume that consumers respond to advertisement stimuli in three ways: cognition, affect, and behavior. Also, they show empirical evidence which confirms previous theoretical claims, found in the psychology, marketing, and communications scholarship, that users avoid advertisement on the Internet due to perceived goal impediment, perceived ad clutter, and prior negative experiences. Based on this theoretical framework, the authors proposed a survey instrument to measure the level of ad avoidance, categorized in three different types (cognitive, affective, and behavioral), as well as its three causal attributes.

In the next subsection, we detail the survey instrument proposed by Cho and Cheon (2004), which has inspired the survey instrument used in this research. However, more than measuring the responses of an online video user *i* to digital ad *j*, our main objective is understanding whether, and in which extent these responses vary with the size and reach of the digital service provider, and with the level of previous engagement of the user with the platform. Equation 5.1 and 5.2 below present the relationships we are interested in estimating empirically.

$$RESP_{i,j} = w(PLAT_i, AD_j, ATTR_i) \tag{5.1}$$

$$RESP_{i,j,PLAT} = g(ENG_{i,PLAT}, AD_j, ATTR_i) \tag{5.2}$$

PLAT identifies the platform providing the service, AD a set of characteristics of the advertisement (e.g., duration, position, etc.), ATTR represents attributes of the user (e.g., age, gender, country of origin, etc.), and ENG a set of variables that captures the level of engagement between the user and the platform service provider in markets other than the online video services. Finally, *RESP* captures the set of alternative outcome response variables by online video users to advertisement already reviewed (e.g., cognitive, affective, or behavioral ad avoidance, ad clutter, etc.).

In Chapter IV, we assumed that tolerance of users to data collection procedures is also dependent on the size and reach of platform service provider, and on the level of engagement of the user with the platform in other markets (see Equation 4.8). Thus, *RESP* also contains a set of variables proposed by Baek and Marimoto (2022) that capture online video users' responses to data collection procedures performed by platform service providers. These variables measure how comfortable a user is when her information is collected, the importance of privacy to the user, her level of concern with how personal information is stored, and with the risk of the platform misusing or sharing personal information without her consent. More details on the scales used to measure such variables are provided in the following subsection.

5.2 Empirical strategy: experiment design, survey instrument, and data summary

This sub-section details how the experiment was designed and implemented to empirically measure the responses of online video users to digital ads and data collection procedures. In addition, the experiment was designed to investigate how the variation in the size of the platform service provider, or in the level of engagement between the user and the provider, affect users' responses. After discussing the experiment design, survey approach, and sampling strategies used, a summary of the data collected is presented.

The experiment used a 2 x 4 design: 2 conditions for market share in the online video market: high vs. low (between variation) x 4 conditions for message repetition, with different sizes of ads and positions in the main content (within variation). A convenience sample of 550 participants[24] recruited through an online panel of general, U.S.-based internet users, was used. Participants first provided basic information on their socio-economic, demographic, and cultural background, their tastes for several types of video content (e.g., sports, cooking, etc.), and their level of engagement with several digital platforms in the market of online videos, and in another markets. Also, they were asked to answer questions to measure users' perceptions regarding the size and reach of several digital platforms and online videos services, and their level of engagement with digital platforms in different markets. This was important to guarantee that the perceptions of the users regarding the size and reach of each platform were coherent with their actual market shares and multi-market present.

Then, participants were randomly split into two groups, A and B. Participants assigned to group A were asked to watch four videos of less than 2 minutes, including ads of different lengths (5, 15, and 30 seconds), and inserted at different positions in the videos (beginning, end middle). The setting gave the impression that the videos were accessed via a well-known video streaming platform (YouTube). Participants randomly assigned to group B were asked to watch the same four videos, but in a setting that gave the impression that the videos were being accessed through an unknown, small video streaming platform (Zen Videos, a brand that was

[24] The selection of participants among those that voluntarily opted to participate in the experiment (seeking for some sort of compensation) followed the objective of achieving geographic, gender, and age quotas representative of typical U.S. internet user.

created just for the experiment). After watching each of the four videos, participants of both groups were asked to answer questions designed to measure their cognitive, affective, and behavioral ad avoidance.[25] They were also asked about the importance of privacy to them and about their concerns related to data collection procedures, storage, and the risks of data misuse or sharing.

The survey instrument, available in the Appendix III of this dissertation, started with a consent form, that explained to participants that the survey is part of an academic study being conducted by the Quello Center at Michigan State University in the United States. Also, it is informed that the study aims to better understand how internet users respond to digital advertising and the collection of personal data by video streaming service providers. It was also highlighted that participation in the survey is voluntary, and that one can withdraw or refuse to answer any question without penalty.

Then, a summary of the topics that will be asked was presented, like demographic information, the participants' tastes for several types of video content, their level of engagement with digital platforms, as well as their impressions after watching four short videos. Finally, the consent form stated that the survey would take approximately 20 minutes, that the answers one provides will not be linked to a person. Finally, the contacts of the supervising Principal Investigator, Professor Johannes M. Bauer, were provided for questions or concerns related to the research project.

After consenting to participate in the survey and answering some screening questions, designed to assure that the participant average characteristics meet geographic, gender, and age quotas that are representative of U.S. internet user, Section 1 of the survey asked the participants

[25] Other responses that cause the ad avoidance, like perceived goal impediment, and perceived ad clutter, were also captured in the survey. As these variables are not relevant to this research, these results were omitted.

questions that assess their level of awareness about video streaming platforms. Then, in Section 2, the level of engagement of the participants is assessed with several online video services. Furthermore, this section assessed their level of engagement with Google in other digital markets and their tastes in different types of videos (e.g., sports, comedy skits, videos about animals, etc.). Finally, participants were asked to disclose the importance of different factors (e.g., quality, price, privacy, etc.) for their choice of which online video service to use.

During Section 3 of the survey, participants watched four different videos with ads embedded and, after each one, they indicated their level of agreement with several statements aimed at measuring participants' level of ad avoidance (cognitive, affective, and behavioral), perceived ad clutter, and perceived goal impediment, among other variables not relevant to this research. It is important to emphasize here that in this Section, participants were distributed randomly in two groups, to watch the four videos in the context of the (fictitious) platform ZenVideos and of YouTube. Two videos had digital ads of 5 and 15 seconds inserted at the beginning of the video, and the two other videos had ads of 15 and 30 seconds inserted at the middle of the video.

Section 4 of the survey asked participants about their level of agreement with several statements regarding privacy concerns. Section 5 collected demographic information (e.g., income, race, and country of origin). The survey concluded with a debriefing statement, where participants were informed that the videos were modified to insert platform brand names at the beginning and advertising at different moments during the videos. Also, they were informed that half of the participants, randomly selected, were told that they were watching videos from YouTube, and the other half was told they were watching videos from ZenVideos, an unknown brand created only for the purposes of the study. Table 5.1 presents a description of the variables assessed with the survey instrument.

Table 5.1 – Description of the variables

Variable Name	Abbreviation	Description
Responses to digital ads		
Overall Ad Avoidance	adavoid	Overall ad avoidance, calculated by the sum of adavoid_affect, adavoid_behav, and adavoid_cog
Ad Avoidance - Affective	adavoid_affect	Average participant's responses to the following two statement: "When I watch a video like this on a video streaming platform like YouTube/ZenVideos, I hate the ads." "When I watch a video like this on a video streaming platform like YouTube/ZenVideos, it would be better if there were no ads." (Strongly disagree = 0; Disagree = 1; Neutral = 2; Agree = 3; Strongly Agree = 4)
Ad Avoidance - Behavior	adavoid_behav	Participant's response to the following statement: "When I watch a video like this on a video streaming platform like YouTube/ZenVideos, I skip the ads if it is possible." (Strongly disagree = 0; Disagree = 1; Neutral = 2; Agree = 3; Strongly Agree = 4)
Ad Avoidance - Cognitive	adavoid_cog	Participant's response to the following statement: "When I watch a video like this on a video streaming platform like YouTube/ZenVideos, I intentionally do not pay attention to the ads." (Strongly disagree = 0; Disagree = 1; Neutral = 2; Agree = 3; Strongly Agree = 4)
Responses to data collections procedures		
Overall Privacy concerns	privacy	Overall privacy, calculated by the sum of priv_collect, priv_import, priv_misuse, priv_safestor, and priv_share
Data collection	priv_collect	Participant's response to the following statement: "I feel uncomfortable when my information is collected without permission." (Strongly disagree = 0; Disagree = 1; Neutral = 2; Agree = 3; Strongly Agree = 4)
Privacy concerns	priv_import	Participant's response to the following statement: "Privacy concerns play an important role in my choice." (Strongly disagree = 0; Disagree = 1; Neutral = 2; Agree = 3; Strongly Agree = 4)
Misuse of data	priv_misuse	Participant's response to the following statement: "I feel concerned about misuse of my personal information." (Strongly disagree = 0; Disagree = 1; Neutral = 2; Agree = 3; Strongly Agree = 4)
Data storage	priv_safestor	Participant's response to the following statement: "I believe that my personal information will not be safely stored." (Strongly disagree = 0; Disagree = 1; Neutral = 2; Agree = 3; Strongly Agree = 4)
Data sharing	priv_share	Participant's response to the following statement: "I believe that my personal information will be afterwards shared without permission." (Strongly disagree = 0; Disagree = 1; Neutral = 2; Agree = 3; Strongly Agree = 4)
Digital ad characteristics		
Ad duration	ad_dur	Duration of the digital ad, in seconds

Ad position	ad_pos	Position of the digital ad inside the video (0 = beginning, 1 = middle)
Streaming platform	str_plt	Streaming platform (0 = Zenvideos; 1 = YouTube)
Participant attributes		
Taste for sports videos	sports	Frequency in which participant watch sports videos. (Never = 0; Rarely = 1; Sometimes = 2; Frequently = 3; Very Frequently = 4)
Perception of YouTube size in context	pu_f_YouTube	Level of perception of how many users YouTube has among family and friends of participants. (Very few = 0; few = 1; some = 2; many = 3; very many = 4)
Perception of YouTube size	pu_YouTube	Level of perception of how many users YouTube has. (Very few = 0; few = 1; some = 2; many = 3; very many = 4)
Importance of ads duration	imp_ads	Level of importance of duration of ads to decision on streaming platform. (Not at all Important = 0; Low Important = 1; Neutral = 2; Important = 3; Very Important = 4)
Importance of previous experience	imp_exp	Level of importance of previous experience to decision on stream platform. (Not at all Important = 0; Low Important = 1; Neutral = 2; Important = 3; Very Important = 4)
Importance of price	imp_pric	Level of importance of price to decision on streaming platform. (Not at all Important = 0; Low Important = 1; Neutral = 2; Important = 3; Very Important = 4)
Importance of privacy	imp_priv	Level of importance of privacy to decision on streaming platform. (Not at all Important = 0; Low Important = 1; Neutral = 2; Important = 3; Very Important = 4)
Importance of quality	imp_qual	Level of importance of quality to decision on streaming platform. (Not at all Important = 0; Low Important = 1; Neutral = 2; Important = 3; Very Important = 4)
Age Group	age_gr	Age group of the participant (1 = 18-34; 2 = 35-54; 3 = 55+)
Gender	gend	Gender (1 = Male; 2 = Female; 4 = Other)
Region	geo	Geographic region of US where participant lives (1 = Midwest; 2 = Northeast; 3 = South; 4 = West)
Country	nation	Country where the participant grew up
Race	race	Race of the participant
Income	income	Income range, in U.S. dollars (< 29999 = 0; 30000 to 59999 = 1; 60000 to 99999 = 2, 100000 to 149999 = 3, >150000 = 4)
Engagement with Google and YouTube		
Engagement with Google	n_serv_goog	Number of Alphabet/Google services used by the participant other than YouTube (Google Maps, Images, News, Chrome, Gmail, Search, and Drive)
Engagement with YouTube	subs_youtube	Participant is a subscriber of YouTube (0 = No; 1 = Yes)
Usage of YouTube	u_youtube	Level of participant’s use of YouTube monthly. (Never = 0; Rarely = 1; Sometimes = 2; Frequently = 3; Very Frequently = 4)

The survey instrument also included attention checks to identify the responses of participants that were not meaningful, which were discarded. Before launching the online survey experiment, a soft launch was performed with 60 participants (who passed the attention checks) to measure the median time for completion of the survey (13.56 minutes). Then, after some calibration on attention checks, the full experiment was launched to collect 550 valid responses. Participants who completed the entire survey and passed all the attention checks were considered as valid respondents, unless they took less than 6.78 minutes to complete the survey (half of the median time of response calculated in the soft launch).

Tables 5.2 and 5.3, and Figure 5.1, provide summary statistics and the distribution of the participants' responses to digital ads and data collection procedures. The summary statistics are shown for all participants, as well as separately for each of the two groups of participants randomly selected to watch the videos in the platforms ZenVideos or YouTube. It is also reported the results of t-tests performed to conduct a preliminary assessment of the existence of statistically significant differences in the mean responses of each of the two groups. The p-values presented in the last column of both tables suggest that the means of all types of participants' responses to digital ads, and of some types of responses to data collection procedures, are different for the two groups. Conclusions based on these differences require a more rigorous statistical investigation, which we report later in this chapter.

Table 5.2 – Responses to digital ads – summary statistics

Experimental observations	All (N=2,200)				Str_plt: ZenVideos (N=1,004)				Str_plt: YouTube (N=1,196)				t-test (Ho: diff = 0)
Variables	**Mean**	**Std Dev**	**Min**	**Max**	**Mean**	**Std Dev**	**Min**	**Max**	**Mean**	**Std Dev**	**Min**	**Max**	**p-value**
adavoid	6.933	3.176	0	12	7.227	3.167	0	12	6.687	3.163	0	12	0.0001
adavoid_affect	2.296	1.119	0	4	2.395	1.103	0	4	2.214	1.126	0	4	0.0001
adavoid_behav	2.610	1.177	0	4	2.685	1.187	0	4	2.547	1.166	0	4	0.0060
adavoid_cog	2.027	1.239	0	4	2.146	1.242	0	4	1.926	1.228	0	4	0.0000

Table 5.3 – Responses to data collection procedures – summary statistics

Experimental observations	All (N=550)				Str_plt: ZenVideos (N=1,004)				Str_plt: Youtube (N=1,196)				t-test (Ho: diff = 0)
Variables	**Mean**	**Std Dev**	**Min**	**Max**	**Mean**	**Std Dev**	**Min**	**Max**	**Mean**	**Std Dev**	**Min**	**Max**	**p-value**
privacy	14.91	3.993	1	20	15.00	4.078	1	20	14.83	3.919	1	20	0.3279
priv_collect	3.013	1.101	0	4	3.068	1.041	0	4	2.967	1.148	0	4	0.0318
priv_import	3.055	0.954	0	4	3.120	0.959	0	4	3.000	0.947	0	4	0.0034
priv_misuse	3.122	0.956	0	4	3.088	0.991	0	4	3.151	0.926	0	4	0.1247
priv_safestor	2.760	1.029	0	4	2.737	1.027	0	4	2.779	1.031	0	4	0.3381
priv_share	2.960	0.985	0	4	2.988	0.968	0	4	2.936	0.998	0	4	0.2210

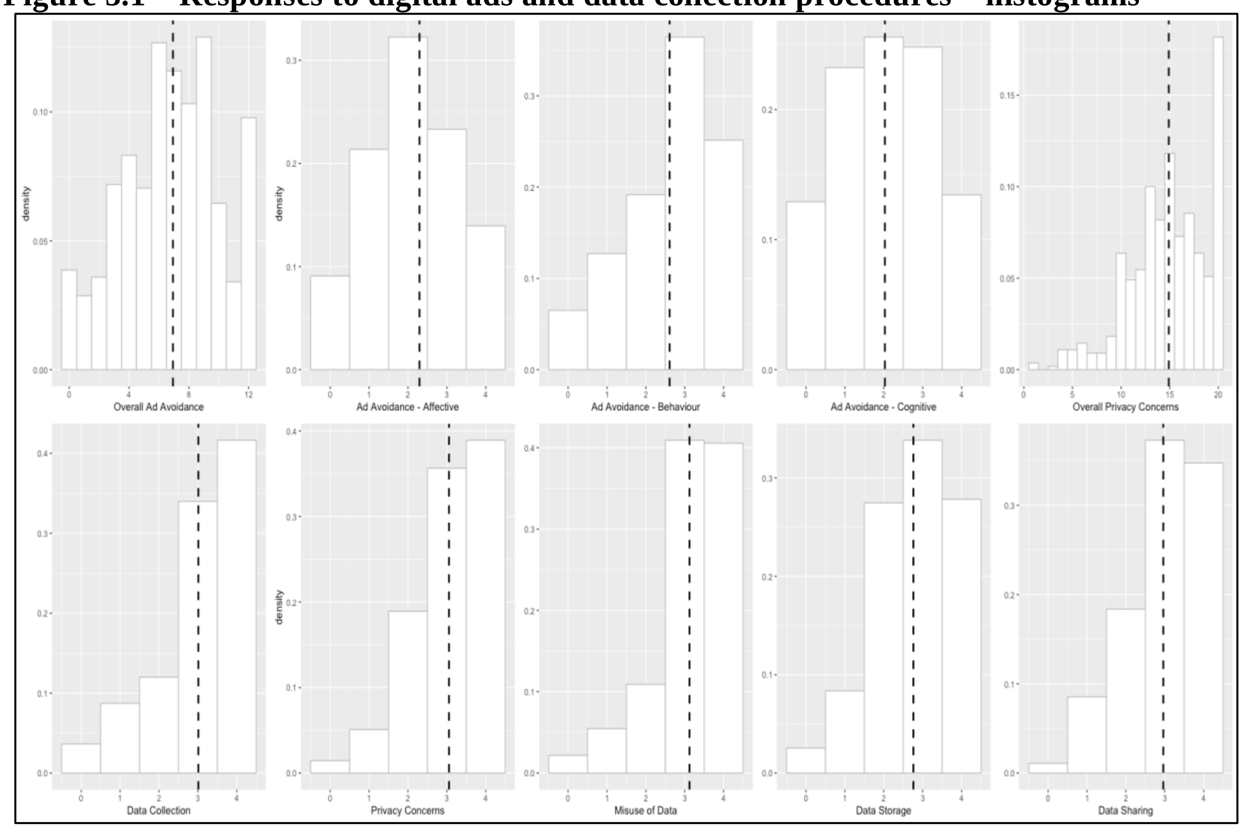
Table 5.4 – Participants' attributes and engagement – summary statistics

Number of participants	All (N=550)				Str_plt: ZenVideos (N=256)				Str_plt: Youtube (N=299)				t-test (Ho: diff = 0)
Variables	**Mean**	**Std Dev**	**Min**	**Max**	**Mean**	**Std Dev**	**Min**	**Max**	**Mean**	**Std Dev**	**Min**	**Max**	**p-value**
Participant attributes													
sports	1.220	1.356	0	4	1.243	1.337	0	4	1.201	1.372	0	4	0.466
pu_f_youtube	2.967	1.209	0	4	2.996	1.183	0	4	2.943	1.230	0	4	0.307
pu_youtube	3.529	0.771	0	4	3.526	0.688	0	4	3.532	0.835	0	4	0.859
imp_ads	2.615	1.074	0	4	2.622	1.077	0	4	2.609	1.072	0	4	0.781
imp_exp	2.796	0.979	0	4	2.849	0.999	0	4	2.753	0.961	0	4	0.022
imp_pric	3.284	0.872	0	4	3.299	0.830	0	4	3.271	0.906	0	4	0.455
imp_priv	3.020	1.030	0	4	3.024	0.990	0	4	3.017	1.062	0	4	0.871
imp_qual	3.347	0.828	0	4	3.375	0.806	0	4	3.324	0.845	0	4	0.158
Engagement with Google and YouTube													
n_serv_goog	4.435	1.918	0	7	4.442	1.832	0	7	4.428	1.988	0	7	0.863
subs_youtube	0.716	0.451	0	1	0.721	0.449	0	1	0.712	0.453	0	1	0.651
u_youtube	2.589	1.413	0	4	2.570	1.368	0	4	2.605	1.449	0	4	0.556

Table 5.5 – Participants' demographic attributes – summary statistics

Number of participants	All (N=550)	Str_plt: ZenVideos (N=256)	Str_plt: Youtube (N=299)
Variables	%	%	%
Participant attributes			
age_gr (18-34)	30.5	30.7	30.4
age_gr (35-54)	31.6	30.7	32.4
age_gr (55+	37.8	38.6	37.1
gend_male	46.0	44.6	47.2
gend_female	53.3	54.6	52.2
gend_other	0.7	0.8	0.7
geo_midwest	19.8	20.3	19.4
geo_northeast	19.5	21.1	18.1
geo_south	39.8	39.4	40.1
geo_west	20.9	19.1	22.4
nation_usa	97.5	97.6	97.3
nation_nonusa	2.5	2.4	2.7
race_white	75.6	80.1	71.9
race_asian	5.3	4.8	5.7
race_latino	4.5	3.6	5.4
race_black	7.1	5.6	8.4
race_others	7.5	6.0	8.7
income (< 29999)	24.3	26.4	22.5
income (30000 to 59999)	32.5	29.3	35.2
income (60000 to 99999)	27.0	24.8	28.9
income (100000 to 149999)	11.1	13.4	9.2
income (>=150000)	5.1	6.1	4.2

Figure 5.1 – Responses to digital ads and data collection procedures – histograms



Tables 5.4 and 5.5 show summary statistics of the attributes of participants, and for their level of engagement with Google and YouTube. The statistics are shown for all participants, as well as separately for the participants of each of the two groups. They mainly suggest that participants' attributes do not differ significatively among the groups. Indeed, the p-values reported in Table 5.4 show that it is not possible to reject the null hypothesis that the mean attributes of both groups of participants are equal, but for variable *imp_exp*[26]. Furthermore, a comparison of the demographic characteristics of the participants of both groups, shown in Table 5.5, corroborates the close similarity between them. These summary statistics confirm the success of the randomization procedure adopted in the experiment to assign participants between the two platforms (ZenVideos and YouTube), with the aim of avoiding strong, statically significant differences in their personal treats.

Summary statistics shown in Table 5.4 for the participants' perception of YouTube size, and their level of engagement with the online video service, and its parent digital platform (Google[27]), also confirm that participants widely perceive and use them as a major player in the online videos market, with a lot of users in the U.S. and among participants' family and friends. Participants of both groups consume on average four digital services provided by Google other than the YouTube service (e.g., Google Maps, Google Chrome, etc.). These results are important to our empirical design, which proposed to compare how the participants' responses to digital ads and data collection procedures vary between a major online video service (YouTube) and a

[26] Although the mean value of *imp_exp* differ between the two groups of participants, this unwanted characteristic of the sample does not interfere on the results of the analysis of the effect of the size and reach of the platform on the participants' responses to digital ads and data collection procedures, reported later in this chapter. This is because, in the estimation models used (see equations 5.3 and 5.4), we control for the effects of this variable on the participants' responses.

[27] Technically, the digital platform is named as Alphabet, but it is more widely known among participants simply as Google. For this reason, the research used the term "Google" to refer for this platform in the survey.

small one (ZenVideos), as well as with the level of participants' engagement of the platform service provider.

5.3. Estimation models

This section specifies the estimation models used to identify associations between the size and reach of the online video platform provider, as well as the level of engagement of an internet user with the platform in other digital markets, and her tolerance to watch digital ads and have their data collected by the platform. As previously shown in this chapter, internet users' responses should be related to attributes of the platform, of the digital ad, as well as of the users themselves (see Equations 5.1 and 5.2).

Through the survey experiment already detailed in this chapter, online video users $i \in \mathrm{I}$ were exposed to four videos with one different digital ad $j \in \mathrm{J}$ inserted in each, of duration ad_dur_j and inserted in the position ad_pos_j of the videos. Then, four types of online video users' responses to digital ads were obtained: $adavoid\_affect_{i,j}$, a$davoid_behav_{i,j}$, a$davoid_cog_{i,j}$, and $adavoid_{i,j}$, which is the overall sum of the three types of ad avoidance measured. Also, the responses of online video users to data collection aspects were gathered and modeled by the variables $priv\_collect_i$, $priv\_import_i$, $priv\_misuse_i$, $priv\_safestor_i$, $priv\_share_i$, and $privacy_i$, which is the overall sum of the five aspects of privacy concerns measured, detailed in Tables 5.1 and 5.3.

The main objective of the estimation procedure was to investigate potential associations between variations in the online videos' platform str_plt_i used, and the users' levels of ad avoidance and concerns about privacy aspects. A second objective was to identify potential associations between the level of engagement of the users with the platform provider in other digital markets, captured by the variable $n\_serv\_goog_i$, and the level of users' tolerance to ads and data collection procedures.[28]

As suggested by the literature reviewed earlier in the chapter, and considering the data collected by the survey experiment, we control for the effect of variations on the platform and on the level of engagement between the user and the platform in other markets. Also, we control for variations in attributes of the digital ads, as well as by several other attributes of the participants. The full list of control variables, denoted as the vector of variables $\boldsymbol{ATTR}_i$, is detailed in Tables 5.1, 5.4, and 5.5. Equations (5.3) and (5.4) below present the estimation models used.

$$RESP_{i,j}^{v} = \varepsilon_i \exp\left(\alpha^{v} + \beta_0^{v} str\_plt_i + \beta_1^{v} ad\_dur_j + \beta_2^{v} ad\_pos_j + \boldsymbol{ATTR}_i \boldsymbol{\gamma}^{v}\right) \tag{5.3}$$

$$RESP_{i,j,str\_plt=1}^{v} = \epsilon_i \exp\left(\delta^{v} + \theta_0^{v} n\_serv\_goog_i + \theta_1^{v} ad\_dur_j + \theta_2^{v} ad\_pos_j + \boldsymbol{ATTR}_i \boldsymbol{\omega}^{v}\right) \tag{5.4}$$

In equations (5.3) and (5.4), $RESP_{i,j}^{v}$ may be either of the nine response variables already detailed, with the superscript v indicating each one. The exponential functional form is the most popular specification when the response variables receive only zero or strictly positive values, and follow an exponential, or a normal distribution (see Figure 5.1). The use of a simple, linear model in this case would suffer from allowing negative outputs of the estimated model, what would be inconsistent with the data observed (Wooldridge, 2010, page 723 and 724).

The coefficients of interest are β_0^{v}, and θ_0^{v}, the semi-elasticities of $RESP_{i,j}^{v}$ and $RESP_{i,j,str\_plt=1}^{v}$ with respect to str_plt_i and $n\_serv\_goog_i$. In other words, they measure the

[28] As the platform ZenVideos were created only for the survey experiment, this secondary assessment was made only with participants who were assigned to watch the videos on Google's YouTube.

average marginal effect on the level of online video users' ad avoidance and concerns with data collection procedures associated with variations in the size and reach of the platform service provider, and in the level of engagement between the user and the platform.

This empirical approach has some intrinsic limitations. First, our data do not allow us to control all the characteristics of the ads that may affect users' tolerance to them. For example, platforms with bigger engagement with the end users can customize the ads shown to each user based on the data collected, to make the ads more interesting for the users. Also, our data do not allow us to control all the users and platform attributes, like time-varying factors, which may affect the users' responses. Examples are cases of data breaches, which may affect user's concerns to privacy issues in the following months, and improvement in the quality of the video content offered, or in the service interface of each platform, which may make users more, or less tolerant to ads and data collection procedures. The implications of such limitations on our empirical approach to the interpretation of the estimation results are discussed in the following sub-section.

5.4. Empirical Results

Table 5.6 and 5.7 show results of the estimation of the models specified by equations (5.3) and (5.4), respectively, using the data collected on the survey experiment already described in this chapter. Table 5.6 reports estimates for the impact of the streaming platform on the types of ad avoidances that were measured. Table 5.7 reports estimates for the impact of the level of engagement of participants with Google in other markets, on the types of ad avoidances measured only among the participants who watched the videos and digital ads on YouTube. Columns (1), (4), (7), and (10) of both tables report estimates calculated using the traditional Poisson quasi-maximum likelihood estimator (QMLE). This procedure gives estimates of the effects of each independent variable on the mean value of the output variable, or, in other words, how the mean value of the ad avoidances measured varies with variations on each independent variable included in the models.

However, one would expect that the effects of variations in the digital platform, and in the level of engagement between the participant and the platform in other markets, on the ad avoidances measured are different among participants with high or low ad avoidance. For example, the effect of variations in the streaming platform, or in the level of engagement with the platform, may be lower for online video users that have low levels of ad avoidance, when compared with those more sensitive to digital ads. If this was true, the estimated partial effects of variations in explanatory variables on the mean value of the ad avoidances might mask different effects in different segments of the ad avoidance distribution.

To investigate the effects of the relevant covariates on features of the ad avoidance distribution other than the mean (for example, in different quantiles), a quantile regression (QR) estimator was used (Wooldridge, 2010). In these estimations, instead of using the exponential models specified in equations (5.3) and (5.4), we use linear model specifications with log-transformed dependent variables, to allow caparison between the resulting estimates and those obtained using the Poisson QMLE estimator. These estimates are reported in Table 5.6 and 5.7 for the quantiles 25% and 75%.

Finally, and for brevity, estimates of just five out of the eighteen control variables used in the estimations are reported in the table. They are the two attributes of the digital ads (ad duration and ad position), and three of the sixteen participant attributes (usage of YouTube, taste for sports, and importance of ads). Table IV.1 in the Appendix IV of this dissertation reports the estimates of all the eighteen control variables used in the analysis reported in column (1), as an example, to allow the review of the full list of same control variables included in all the estimations reported in Tables 5.6 and 5.7.

The results show a negative, statistically significant association between platform size and all types of ad avoidance. In other words, the results suggest that the higher the size, or the market share of the platform, the lower a user's ad avoidance or nuisance cost to digital ads, even after controlling for digital ads attributes and participant's attributes. The mean overall ad avoidance of the survey participants who watched the videos on the incumbent platform (YouTube) is 6.55% lower than of the participants who watched through the small platform (ZenVideos), with results statistically significant at the 1% level, and with a 95% confidence interval of [-10.3%, -2.76%]. These results are also consistent for all three types of ad avoidances that were investigated. Mean affective ad avoidance is 6.2% lower for YouTube users, while the mean behavioral ad avoidance is 4.13% lower, and the mean cognitive ad avoidance 10% lower. The results support the assumption made in Chapter IV of this dissertation that participants' nuisance costs of watching ads are lower the higher the size and reach of the platform (see Equation 4.7).

The investigation of the effects of platform variation on the quantiles of the ad avoidances distributions suggests that the impact is higher in magnitude for participants with high levels of ad avoidances. Although the effects on the quantiles 25% and 75% of the overall ad avoidance do not differ significatively with respect to the effect on the mean (7.59% and 5.10%, respectively), the results are quite different for the three types of ad avoidances analyzed in separate. The effect of platform variation on the 25% quantile of all the three types of ad avoidances are not statistically different than zero, while the 75%

quantile of the affective ad avoidance, and of the behavioral ad avoidance are 5.69% and 4.62% lower, respectively, among participants who watched the videos through the YouTube platform, when compared to those that watched through ZenVideos.

Table 5.6 – Results of the Poisson estimation – Effects of variance on the streaming platform

Dependent variable	Ad Avoidance			Affective Ad Avoidance		
Model	(1)	(2)	(3)	(4)	(5)	(6)
Method	P-QLME	QR25%	QR75%	P-QLME	QR25%	QR75%
Str. Platform	-0.0655***	-0.0759**	-0.0510***	-0.0620***	-0.0251	-0.0569***
	(0.0193)	(0.035)	(0.0167)	(0.0204)	(0.0307)	(0.0171)
Ad duration	-0.0048***	-0.0074***	-0.0039***	-0.0053***	-0.0053***	-0.0030***
	(0.0014)	(0.0022)	(0.0012)	(0.00147)	(0.00198)	(0.00115)
Ad position	0.207***	0.296***	0.157***	0.255***	0.313***	0.182***
	(0.0248)	(0.0364)	(0.0206)	(0.0261)	(0.0365)	(0.0237)
Use of YouTube	-0.0506***	-0.0695***	-0.0271***	-0.0550***	-0.0835***	-0.0336***
	(0.0105)	(0.0179)	(0.0092)	(0.0112)	(0.0156)	(0.0083)
Taste for sports	-0.0788***	-0.108***	-0.0538***	-0.0821***	-0.0996***	-0.0517***
	(0.0096)	(0.0188)	(0.0078)	(0.0102)	(0.0169)	(0.0080)
Import. of Ads	0.0536***	0.0577***	0.0505***	0.0636***	0.0847***	0.0613***
	(0.0115)	(0.0173)	(0.0093)	(0.0123)	(0.0159)	(0.0093)
Observations	2120	2048	2048	2120	2000	2000

Dependent variable	Behavioral Ad Avoidance			Cognitive Ad Avoidance		
Model	(7)	(8)	(9)	(10)	(11)	(12)
Method	P-QLME	QR25%	QR75%	P-QLME	QR25%	QR75%
Str. Platform	-0.0413**	0.0463	-0.0462***	-0.100***	-0.0786	0.0000
	(0.0193)	(0.0349)	(0.0134)	(0.0265)	(0.0727)	(0.0151)
Ad duration	-0.0039***	-0.0059**	-0.0025***	-0.0056***	-0.0004	0.0000
	(0.0014)	(0.0026)	(0.0009)	(0.0019)	(0.0053)	(0.0009)
Ad position	0.154***	0.172***	0.0963***	0.221***	0.0658	0.0000
	(0.0251)	(0.0436)	(0.018)	(0.034)	(0.0964)	(0.0214)
Use of YouTube	-0.0278***	-0.0345*	-0.00598	-0.0746***	-0.0781*	0.0000
	(0.0106)	(0.0187)	(0.00765)	(0.0139)	(0.0408)	(0.00873)
Taste for sports	-0.0758***	-0.0892***	-0.0471***	-0.0792***	-0.0888***	0.0000
	(0.00957)	(0.0172)	(0.00595)	(0.0131)	(0.0339)	(0.00945)
Import. of Ads	0.0514***	0.0808***	0.0521***	0.0454***	0.0707**	0.0000
	(0.0111)	(0.0219)	(0.00782)	(0.0162)	(0.0348)	(0.00806)

Observations	2120	1978	1978	2120	1840	1840

Columns report results of Poisson QLME estimations of the effects of variations of explanatory variables on the mean of the output variables, as well as on their 25% and 75% quantiles.

For quantile regression estimates reported, outcome variables were log transformed.

Robust standard errors are reported in parentheses.

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

The partial effects of some digital ads and participant attributes on ad avoidances are also interesting to discuss. For example, although the effects of an increase in the ad duration on the levels of ad avoidance are negative (between 0.3% and 0.6% for each additional second), the greater the relevance of ads duration to the participant's decision on which streaming platform to use, the greater the participants ad avoidance levels. A reasonable explanation to these incongruent results is that although the participants consider that longer ads impede them to consume the relevant content, longer ads may have more room to catch the user's attention and interest. However, these results are not conclusive, as only three ad durations were tested in this experiment (5s, 15s, and 30s).

Digital ads placed in the middle of the videos are associated with a 15.4% higher mean overall ad avoidance than when the ads are placed at the beginning of the video, confirming early studies already reviewed in this chapter. This effect is even greater for the mean affective ad avoidance, which is 25.5% higher for ads placed in the middle of the ad. In another interesting result, ad avoidances are consistently lower the higher the frequency of participants usage of YouTube, suggesting that the previous experience with a digital ads based online videos platform reduces the harm of ads to internet users regardless of the platform, a result also consistent with the literature reviewed. Finally, the negative associations found between the taste for sports videos (the theme of all the four videos watched by each participant), and the ad avoidance levels suggest that the interest of the user to the video content attenuates the disutility generated by the ads.

Table 5.7 brings results estimated only among participants who watched the videos on the YouTube platform. The objective of performing these estimations was to assess the effects on the levels of ad avoidance that can be associated with the participants' level of engagement with YouTube's parent platform, Google, in other digital markets. The estimation methods were the same used in the models reported in Table 5.6, as well as the control variables. Results found for the control variables were omitted for brevity.

Table 5.7 – Results of the Poisson estimation – Effects of engagement with Google in other markets

Dependent variable	Ad Avoidance			Affective Ad Avoidance		
Model	(1)	(2)	(3)	(4)	(5)	(6)
Method	P-QLME	QR25%	QR75%	P-QLME	QR25%	QR75%
Number of Google Services	-0.0212***	-0.0299***	-0.0206**	-0.0102	0.0051	-0.0165**
	(0.0078)	(0.0112)	(0.0080)	(0.0084)	(0.0157)	(0.0073)
Observations	1136	1089	1089	1136	1060	1060

Dependent variable	Behavioral Ad Avoidance			Cognitive Ad Avoidance		
Model	(7)	(8)	(9)	(10)	(11)	(12)
Method	P-QLME	QR25%	QR75%	P-QLME	QR25%	QR75%
Number of Google Services	-0.0303***	-0.0535***	-0.0187***	-0.0214*	-0.0176	-0.0346***
	(0.0079)	(0.0128)	(0.0054)	(0.0111)	(0.0237)	(0.0053)
Observations	1136	1050	1050	1136	965	965

Estimations were performed only among participants who watched the videos in the YouTube platform.
Columns report results of Poisson QLME estimations of the effects of variations of explanatory variables on the mean of the output variables, as well as on their 25% and 75% quantiles.

For quantile regression estimates reported, outcome variables were log transformed.

Robust standard errors are reported in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

The reported estimates suggest that the higher the number of digital services consumed by participants from Google (other than YouTube), the lower their level of ad avoidance. The mean overall ad avoidance of participants is 2.12% lower for each other digital service the participant consumes, with the results statistically significant at the 1% level, and a 95% confidence interval of [-3.65%, -0.58%]. Similar results are found for the mean affective ad avoidance, behavioral ad avoidance, and cognitive ad avoidance, which are 1.02%, 3.03%, and 2.14% lower for each other digital service consumed, respectively. These results also corroborate the assumption made in Chapter IV of this dissertation that the participants' nuisance costs of watching ads (their tolerance to ads) is lower the higher the level of engagement between the platform and the participant in other digital markets.

Analyzing the results of the quantile regressions, is it possible to also note that, although the effect of a higher participant – platform engagement on 25% and 75% quantiles of the overall ad avoidance are virtually the same (-2.99% and -2.06%, respectively), some important variation is found for the three different types of ad avoidances. For the affective ad avoidance, and the cognitive ad avoidance, the effects of the level of engagement on quantile 25% are not statistically different than zero, while are highly statistically significant on quantile 75% (-1.65% and 3.46%, respectively). On the other hand, the effect on quantile 25% of the behavioral ad avoidance is almost three times higher than the effect on quantile 75% (-5.35%, and -1.87%, respectively), suggesting that no strong conclusions can be made by comparing the effects on the different segments of the ad avoidances' distributions.

Table 5.8 shows results of the Poisson QLME estimation of the effects of platform, and engagement variations on the mean participants' responses regarding data privacy concerns. In the estimation models (1) to (6), the explanatory variable of interest is the streaming platform in which the participant watched the videos. In the other models, this explanatory variable is replaced by the one which measures the number of Google digital services used by the participant other than the YouTube. Also, models (7) to (12) were estimated using only data of participants that used the YouTube platform in the experiment. For all models, the same control variables included in Table III.1 were used, but the variables which capture attributes of the digital ads (ad duration, and ad position). The exclusion of these two variables was done because the privacy related survey is administered once per participant, and so the answers do not vary with the digital ads attributes.

Table 5.8 – Results of the Poisson estimation – Effects of platform and engagement on privacy concerns

Dependent variable	Overall Privacy	Data collection	Privacy concerns	Misuse of data	Data storage	Data sharing
Model	(1)	(2)	(3)	(4)	(5)	(6)
Str. Platform	-0.0074	-0.0385**	-0.0322**	0.0281**	0.0213	-0.0156
	(0.0110)	(0.0157)	(0.0127)	(0.0128)	(0.0160)	(0.0143)
Observations	2120	2120	2120	2120	2120	2120
Model	(7)	(8)	(9)	(10)	(11)	(12)
Number of Google Services	-0.0113***	-0.0005	-0.0032	-0.0014	-0.0312***	-0.0215***
	(0.0041)	(0.0059)	(0.0055)	(0.0045)	(0.0061)	(0.0055)
Observations	1136	1136	1136	1136	1136	1136

Columns report results of Poisson QLME estimations of the effects of variations of explanatory variables on the mean of the output variables.

The same control variables included in Table III.1 are presented in all the twelve models reported in this table, but the variables which capture attributes of the digital ads (ad duration, and ad position), as the privacy related survey is administered once per participant, after her have watched all the videos.
Robust standard errors are reported in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

The estimates reported in Table 5.8 suggest that the higher the size and reach of the platform, and the level of engagement between the platform and the user in other digital markets, the lower the user's privacy concerns. Although the overall data privacy concerns of the experiment participants are note related to the platform they used, the level of harm created when participants' data is collected without permission is 3.85% lower among participants which used the YouTube platform, when compared to those who used ZenVideos, a result statistically significant at the 1% level.

Participants who used the YouTube platform reported a lower importance of data privacy concerns for their choice of platform. Their level of concern about misuse of personal data were 3.22% and 2.81% lower. On the other hand, no statistically significant effects were found for the effects of platform variation on participants' concerns with data storage and sharing. Furthermore, we found that the overall privacy concerns of the experiment participants who were assigned to use the YouTube platform are 1.13% lower for each digital service they use from Google other than YouTube. The effect is even higher for the participants' concerns about the risk that personal information might not be safely stored, or shared without permission, which are 3.12% and 2.15% lower per each other Google digital service used.

5.5. Discussion and main takeaways

The results of these survey experiments suggest that the higher the size, or the market share of a digital platform, the lower the ad avoidance and the privacy concerns of their users, after controlling for the attributes of the participants and of the digital ads. A deeper investigation of the effects of platform variation on quantiles of the ad avoidance distributions allowed us to conclude that this association is higher in magnitude for participants with high levels of ad avoidance. Also, the results of our survey experiment suggest that the higher the number of other digital services of the same digital platform consumed by an online videos user, the lower their levels of ad avoidance and data privacy concerns with respect to that platform.

These results provide empirical grounding for the assumptions made in Chapter IV about the proportionally inverse relationship between the user's nuisance cost to digital ads and data privacy concerns, and the market share of the platform and the number of other markets where the platform is present (see Equations 4.7 and 4.8). However, some limitations of this research should be recognized. First, our experimental design just included two platforms, a well-known incumbent, and a totally unknown, small platform created just for the experiment. This set up does not allow us to control for characteristics of digital platforms other than their market share. Differences in the participants ad avoidance and data privacy concerns for each platform may not be as significant if YouTube were compared with a middle-sized platform, or with a group of platforms of different market sizes. Further research should investigate such relationships with a wider set of platforms.

Also, the relationship between the level of engagement of users with the platform in other markets, and their responses to digital ads and data privacy concerns should be investigated for platforms other than Google, to allow further generalization of the results. Finally, it is important to note that the experiment design focused on investigating the nature of the reactions of online video users to digital ads (in video format). Although this is a common case set up to represent users' daily interactions with digital ads and data collection procedures, the investigation of these relationships in other ads-based services, like social media and search engines, for example, should be done before generalizing our results to the entire digital economy.

Despite of these limitations, the results of the survey experiment generated theoretically and methodologically robust findings to establish a possible path for policymakers and competition authorities that are investigating the channels through which big digital platforms may exploit their market power. It reveals scenarios in which platforms could earn supra-normal profits by collecting more than the optimal level of data and inserting more than the optimum level of digital ads. Along with the conceptual models proposed in Chapter IV of this dissertation, these empirical results suggest that big, multi-market digital platforms can collect more data and insert more ads on their digital services, because their end users are more tolerant to these strategies than the users of smaller, or single-market platforms. An above-equilibrium level of digital ads and data collection procedures may reduce the utility that the end users could attain in a competitive scenario. It should also represent a competitive advantage for incumbent big techs, which hardly can be overcome by market-specific, competition policy and antitrust remedies.

On the other hand, our results may also suggest that concentration in some digital markets is welfare-enhancing. For example, keeping the level of ads and data collection procedures the same throughout the online videos' platforms, these sources of disutility would generate less harm to the welfare of end users if the market were dominated by a big, multi-market incumbent, than if it is served equally by several platforms under perfect competition. The conclusion has implications for the adoption of ex ante versus ex post competition policies to promote competition for the incumbent, digital platforms, as will be discussed in Chapter VI of this dissertation.

This research may also inform competition authorities on the design of tools to assess market power, and to delineate the boundaries of relevant, digital markets. For example, empirical investigations of end user responses (in terms of ad avoidance and privacy concerns) to small increases in the level of digital ads inserted, or in the level of data collected or shared by a digital platform could use this approach. The SSNIA and SSNID tests proposed in Chapter IV could use the empirical approach presented here, for example, similar experimental designs, scales, and survey instruments.

CHAPTER VI – EMERGING POLICY AND REGULATORY REGIMES

The rise of digital platforms, both as a critical infrastructure and an increasingly important business model in the digital economy, has stirred the debate among scholars and policymakers around the world. The internet has had positive impacts on competition, investment, and innovation in many industries. However, big technology companies increasingly act both as intermediary platforms and as providers of services and goods. A central concern is whether the prevailing market-oriented public policies and institutional practices for digital networks and services continue to be appropriate to realize the benefits of information technologies for society. Moreover, their ability to shape the architecture of markets in which they also compete creates incentives to design rules to their own benefit (Ezrachi & Stucke, 2016). The high market shares of platforms in several digital markets have heightened concerns about potential harms to competition and innovation, as well as broader social implications, including the democratic political debate and the future of traditional media industries.

Such concerns have motivated scholars and governments to reconsider how competition policy and regulation can promote competitive digital markets. The approval of the Digital Markets Act (DMA) by the members of the European Union has already been stimulating competition policy and regulatory reforms in other parts of the world, like Latin America and Asia.[29] Regulatory authorities in countries with lower capacity to develop an approach targeted to national conditions may be tempted to simply imitate provisions of the new European toolkit.

[29] For the purposes of this dissertation, we will consider the Digital Markets Act as motivated by competitive concerns. Some experts have argued that it is an instrument of trade policy disguised as competition policy.

A similar effect happened with the General Data Protection Regulation in 2016, where it was aggravated by the adequacy provisions required to exchange data with Europe.

The temptation to emulate DMA will be particularly strong for agencies with constrained power and resources to conduct independent analyses of digital markets and the behavior of incumbent platforms. However, platform policy requires careful analysis due to a multitude of potential positive and negative effects on innovation, investment, and on the dynamics of digital markets. These may unfold differently depending on the developmental trajectories and market conditions of a country. Promoting competition in the platform economy may therefore demand variations in policy and regulatory regimes (Cioffi et al., 2022).

This chapter presents a comparative analysis of the main policy and regulatory regimes[30] currently suggested in the research literature to promote competition in digital markets, and their tradeoffs. In this exercise, we highlight what should be considered by policymakers to define the regimes better suited for the local context of each country.

In Chapter II we set the stage, with a discussion regarding the causes of the concentrated market structure of digital markets and the trade-offs it raises. Building on these insights, here we differentiate structural vs. behavioral remedies, and their complementary objectives of promoting competition *on* and *for* the incumbent digital platforms. The first objective focuses on promoting competition in markets served by dominant digital platforms (e.g., competition among sellers in e-commerce platforms, among drivers in ride-railing platforms, etc.). The second aims at promoting competition for these dominant digital platforms (see Crémer et al., 2019).

A spectrum of policy and regulatory regimes is then compared that ranges from stringent precautionary competition policy and traditional ex ante regulatory remedies to ex post

---

[30] The term policy and regulatory regimes refers to a set of public policies, regulations, executive orders, statutes, rules, and other institutional arrangements created for addressing a policy problem (May & Jochim, 2013).

competition policy enforcement, ex post regulation and various self-regulation and co-regulation mechanisms. Finally, we provide a scenario-based analysis of the effects of adopting different policy and regulatory regimes. The analysis considers the context of different stages of development of the digital economy and the need to promote investment, innovation, and large-scale adoption of digital services by the end-users. We sketch four typical countries' economic and developmental scenarios and discuss the adoption of each alternative regime to promote competition in the local digital markets, as well as the main challenges to their implementation by policymakers.

This conceptual analysis of different objectives and regimes (which can be adopted exclusively or in combination) offers several insights. With regards to alignment between platform policy and regulatory models and national conditions, we argue that no single best regime exists that can promote competition and innovation in digital markets of every country. Rather, the analysis suggests that national and regional conditions (e.g., the developmental phase of the digital economy, the landscape of potential players) interfere in the efficiency of alternative competition policy and regulatory regimes to promote competition without harming incentives for innovation and investment. Consequently, national policymakers and regulators would be well-advised to adopt customized approaches that consider the country's digital economy and institutional context.

Furthermore, the analysis suggests that in most countries, ex post competition policy approaches might provide a good balance between promoting competition through increased contestability without harming incentives for innovation. Ex ante remedies must be cautiously assessed, as their effectiveness is very dependent on a country's economic conditions, like the existence of a robust innovation ecosystem, with abundant venture capital and skilled workforce, besides of a well-developed digital ecosystem. On the other hand, ex ante regulatory regimes can promote competition in several scenarios, and they also should be used to promote local innovation and development when incumbent platforms are foreign big techs.

This analytical exercise contributes to the debate on how policymakers and regulatory authorities should act to safeguard competition in digital markets, protecting the strong benefits brought by the incumbent, intermediation platforms, and the incentives for innovation in the digital economy. It may serve as a tool to guide policymakers and regulators to decide about which policy and regulatory approaches are more suitable to their own context and objectives.

The remainder of this chapter is organized as follows. Section 6.1 discusses different objectives policymakers and regulators can adopt to guide the design of interventions aimed at promoting competitive digital markets. Section 6.2 presents and discusses the five main competition policy and regulatory regimes proposed so far by the research literature to deal with platform dominance in the digital economy. In Section 6.3 we outline and discuss four scenarios that represent the conditions of countries at different stages of digital ecosystem development. In this section we also examine the appropriateness, and efficiency of each of the policy regimes in these scenarios. Section 6.4 discusses relevant implementation challenges that competition policy and regulatory authorities must overcome when intervening to promote competition in digital markets. Section 6.5 concludes the chapter with a summary of main takeaways, and directions for future research.

6.1 Objectives of policy and regulatory interventions

Considering the possible welfare-enhancing and welfare-reducing effects of concentration in digital markets, it is important to understand how different policy and regulatory measures affect them. Are there trade-offs that need to be balanced? Can policy reconcile vibrant competition with the generation of sustained levels of investments and innovation? A first step in this analysis is a clarification of whether the overarching objective of a policy intervention is to foster competition *on* digital platforms or to foster competition *for* the digital platforms (Crémer et al., 2019).

Competition on the digital platforms

Digital platforms are among the main providers of digital services to end users and suppliers in today's economy. Because they have considerable discretion over the architecture of the electronic transactions in which they partake, they both create and regulate marketplaces that are used by billions of people and companies worldwide. By enabling greater scalability of small businesses, reducing the costs of communication, and enabling other entrepreneurs to experiment with platform features and capabilities to distribute services and reach new customers, these platforms have enabled increased competition and innovation in several on-line and off-line markets.

On the other hand, this central hole played by the platforms gives them access to privileged information related to demand and supply of many different businesses that use their platforms to trade. In scenarios of limited competition for the intermediation platform, such advantages may create incentives for incumbent platforms to behave anticompetitively (e.g., self-preference of their products on search results, enter exclusivity agreements with selected suppliers, etc.). Cusumano et al. (2021) explain that the absence of clear boundaries to the operation of incumbent digital platforms creates incentives for a strategic abuse of their intermediate position that may create o form of moral hazard, as platforms may exploit users on both sides of the intermediation business with relatively weak adverse consequences.

Therefore, an objective of policymakers should be to create measures to guarantee that the rules and conduct imposed by incumbent platforms on participants in their own marketplaces do not distort free and vigorous competition and the incentives to innovation on both sides of the intermediation platform. A range of policy interventions, including legislation, ex ante or ex post regulation, or co-regulation are principally capable to deal with specific aspects of the operation of marketplaces created by the incumbent platforms, even though their effectiveness likely varies. Examples are regulation to limit self-preferencing on the distribution of services and goods, transparency mandates on algorithms employed to determine exposure of different products on platforms, boundaries on data collection and processing, the creation of codes of ethics on the use of artificial intelligence, among others.

A key question, however, is whether such interventions are needed to safeguard efficient market operations, or whether platforms understanding the interdependencies and complementarities in their business ecosystems do have sufficient incentives to balance interests. Also, suitability of ex ante vs. ex post interventions should be weighed considering the tradeoff between the aim for immediate welfare gains to consumers and the creation of rigid regulatory structures over very dynamic markets, which may end up limiting innovation and harming consumers' welfare.

Competition for the digital platforms

Fostering competition for the intermediation platforms may require competition policy and/or regulatory measures that can promote the contestability of existing platform markets, the entry of new players into the intermediation business, or that reduce switching costs for end users. Most approaches to promote competition for the platforms assume that the long-term net outcome of concentration in digital markets diminishes welfare. Consequently, policy and regulatory interventions should be designed to increase competition for the intermediation role, while protecting the incentives of incumbent platforms to innovate and invest. Other economists, arguing from different notions of what conditions characterize effective, dynamic competition, pose that concentration per se does not mean lack of competition, and that interventions should be designed with the aim of increasing contestability to incumbent intermediation platforms.

One of the challenges in technologically dynamic systems is to identify the conditions under which competition is workable. Theoretical and empirical research shows that both too little competition and too intense competition can lower rates of innovation. The optimal intensity of competition varies by innovation type (e.g., Aghion et al., 2005; 2021). It is likely higher for modular, incremental innovations (e.g., apps, edge innovations) but lower for architectural innovations (e.g., innovation into data infrastructures) (Bauer and Knieps, 2018). Thus, there is no single threshold for market concentration that can serve as a rule of thumb to inform further investigation of a case.

The most common approaches start with a delineation of which markets are to be addressed, followed by the adoption of clear criteria for identifying the presence of market power in those markets. Alas, the operationalization of market power in the platform economy and the methods to define which digital platforms and markets should be targeted by pro-competitive remedies, remain contentious, as discussed in Chapter IV of this dissertation. For example, Scott-Morton et al. (2019) and U.K. Treasury (2019) argue that the traditional conceptualization of market power needs to be re-defined in the context of digital markets.

In traditional markets, power is approximated by the ability of a firm to increase and sustain prices above the competitive equilibrium. In digital markets, such as search, retail prices for customers are often zero but competitive advantages and entry barriers are often created by the accumulation and control of customer data and by gaining customer attention (i.e., time spent on the platform). These new digital assets should be considered in the analysis of digital market power.

Another challenge to the promotion of entry and contestability in digital markets, that has been recently begun to be explored by the literature, is the existence of "incumbency advantages" resultant from the strong network effects that characterize several markets, like social media and messaging (Biglaiser et al., 2022). The authors explored theoretically what may prevent users to switch to another platform, even if it offers better services. They mainly found that, for social media users, the utility of switching to a superior service is only compelling if a relevant portion of users switch, which is unlikely due to lack of coordination among them. However, when users multi-home, the likelihood of users to switch is increased because they can adhere to the new service without losing access to the incumbent one. Consequently, according to the authors, regulatory measures to combat platform attempts to reduce end user's ability to multi-home should help keeping digital markets competitive.

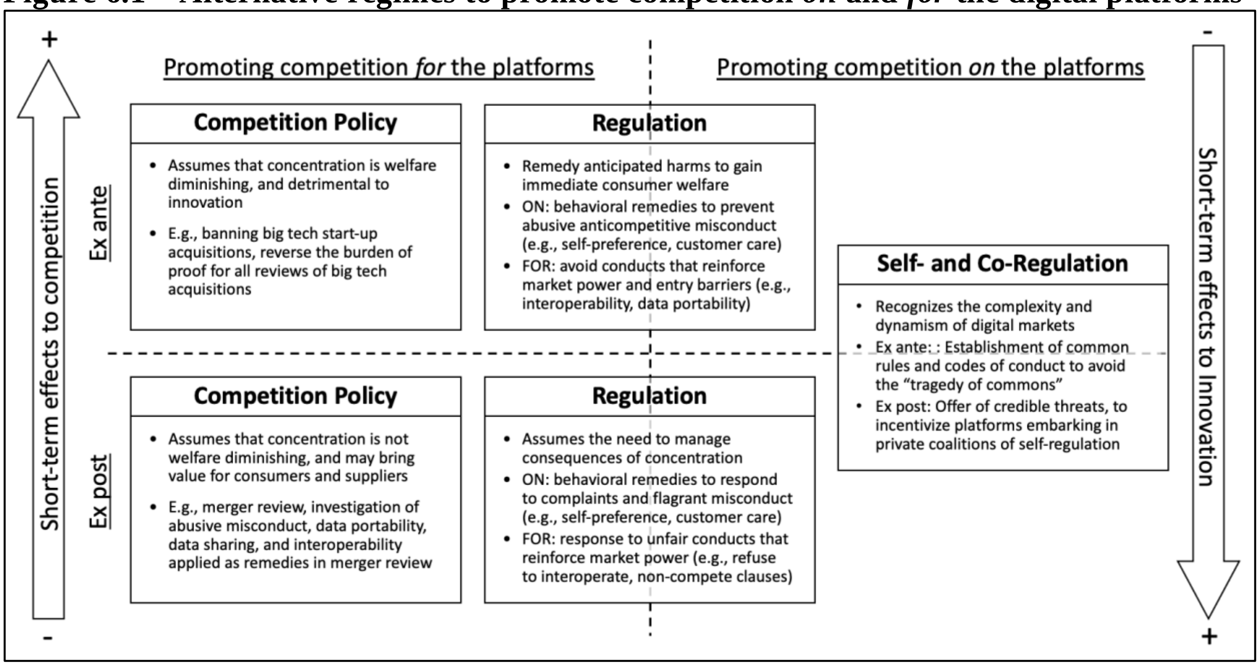
The empirical research reported in Chapter V of this dissertation corroborates the claim for the existence of "incumbency advantages". We showed that the size and multi-market presence of online video platforms affects the level of disutility generated by the insertion of digital ads, and the adoption of data collection procedures. Applied to the debate on how to promote competition for the platforms, these results suggest that end users would hesitate to switch from an incumbent to a small platform competitor even if the later offers a service with fewer digital ads or less egregious data collection practices

6.2. Alternative competition policy and regulatory regimes

Several alternatives are proposed by the research literature to design competition policy and regulation to achieve these complementary objectives of promoting competition *on* and *for* the digital, intermediation platforms. The spectrum of measures ranges from stringent precautionary competition policy and ex ante regulatory remedies to less intrusive self-regulation and co-regulation. In between these extremes are forms of reformed ex post competition policy enforcement and ex post regulation. The selection of one of these alternatives, exclusively or in combination, requires careful comparative evaluation and balancing. Figure 6.1 provides a summary of the five main competition policy and regulatory regimes found in the recent research literature, their most common objectives, and their tradeoffs for stimulating competition preserving the innovation incentives of dominant firms.

Although both sets of ex ante and ex post interventions reviewed are designed with the aim of promoting competition and investment in innovation in the long-term, they differ on their likely short-term effects. For example, ex ante measures targeting large-scale, incumbent platforms are aimed to generate increased incentives for entry in the platform intermediation market, and reduced switching costs for users and sellers. This should create positive, short-term effects to competition *on* and *for* the platforms, contingent to the existence of some exogenous, microeconomic pre-conditions (discussed in the next Section). This increased competitive pressure may create incentives to ramp up investments in innovation in the medium and long-term. On the other hand, the incentives of incumbent platforms to keep up their innovation activities may be reduced in the short-term, because of the prospects of having to share the efficiencies, and potential profits generated by them. As a result, incumbent platforms may invest less in innovation or change the course of it, with negative consequences for the entire innovation ecosystem, as incumbent platforms are responsible for a large share of the total investment in innovation.

Figure 6.1 – Alternative regimes to promote competition *on* and *for* the digital platforms



Thus, while short term and long-term effects of each alternative regime likely diverge, whether the net outcome for society is positive or not will depend mainly on two factors: i) the potential increase in the rate of investment in innovation in the future due to the entry of new players relative to the decrease of investment in innovation in the short-term; and ii) the social discount rate applied to future investment in innovation. Policymakers and regulators must find a balance between protecting the benefits created by incumbent digital platforms and mitigating the risks to innovation and investment that may be associated with a concentrated market structure. The following subsections provide a detailed review of each of the competition policy and regulatory regime depicted in Figure 6.1.

Self-regulation and co-regulation

Self-regulation measures are suited for cases where competition policy and regulatory enforcers aim at promoting healthy competition on the platforms but recognize that in very complex, fast-moving dynamic markets, the transaction costs and risks associated with imposing ex ante and/or ex post regulatory measures are high. Also, supporters of the adoption of self-regulation alternatives consider that the concentrated structure of digital markets frequently has welfare enhancing characteristics, although it may eventually create room for abusive misconduct by digital platforms with market power.

Furthermore, dominant digital platforms may have incentives to engage in self-regulation to avoid rigid government oversight (Cusumano at al., 2021). According to the authors, incumbent platforms would be motivated to take steps toward creating private coalitions for the establishment of common rules (e.g., interoperability standards) and codes of conduct to avoid a scenario similar to a tragedy of the commons.

In fact, among digital platforms, the common source of prosperity so far is the trust of society (government authorities, sellers, and end users) on platforms' legitimate intention of profiting from the provision of extremally welfare-enhancing digital products and services. Non-myopic firms have incentives to protect that common interest, while others may deliberately play a short-term, profit maximization strategy through abusive misconduct, that will push authorities to impose ex ante measures on all the incumbent platforms. The authors assert that self-regulation, encouraged by credible threats and pressure from policymakers and competition policy authorities, could prevent a tragedy of the commons scenario and generate better outcomes than traditional competition policy and regulatory remedies.

As a more rigid approach in this context, co-regulation creates a supervised, or certified, self-regulation regime (Marsden, 2011). Private stakeholders propose boundaries to their own conduct to regulatory authorities, and these boundaries are monitored by a trusted, third-party compliance framework. Articles 40 and 41 of the General Data Protection Regulation (GDPR), the European digital privacy regulatory framework, are an example of a co-regulation framework. They establish codes of conducts (soft law) and appropriate forms of oversight that can be proposed by private stakeholders. von Grafenstein (2022) analyses this regime and concludes that it provides a balanced approach. It is suited for addressing the need of a less rigid, but still effective regulatory regime that avoids misconduct of dominant players, without harming too much the incentives for them to keep innovating.

Precautionary (ex ante) competition policy

The broader use of ex ante competition policy remedies is a relatively recent phenomenon in the U.S. and Europe, and it has primarily envisioned to foster competition for the incumbent intermediation platforms. It assumes that the degree of concentration and associated distortions of competition allow incumbent platforms to appropriate users' and consumers' surplus. Moreover, concentration is, prima facie, considered detrimental to the pace of innovation in the long run. Theoretically, this approach is inspired by the ideas underlying Arrow's "replacement effect", which asserts that imperfect competition and market power reduce innovation incentives (Gilbert, 2020 p.6). This effect was demonstrated formally in a highly simplified model setting. Even though one could question the applicability to the platform economy, it has provided a rationale for policymakers to foster contestability of and entry in the platform business, with the expectation that competition will not affect the investment in research & development (R&D) by the incumbent platforms.

However, this application of a precautionary approach may have effects that reduce investment in innovation in the short-run and should therefore be examined carefully. First, the digital economy is in constant evolution, and there are vast opportunities of product differentiation in digital markets. This may render ex ante measure outdated very quickly. For example, Haucap and Heimeshoff (2014) discuss measures to foster competition for a platform, using Skype as an example of a quasi-monopolist with an impenetrable competitive position. Without competition policy or regulatory interventions, entry and product differentiation have given rise to communication platforms that captured a significant market share from Skype.

Second, the tools to define i) the markets to be addressed, ii) the platforms with market power, and iii) the right remedies to foster competition for the intermediation platforms are not well-stablished in the research literature and in practice (as discussed in Chapters IV and V of this dissertation). Furthermore, the potential harms to innovation and social welfare in the long-term arising from the concentrated market structure of the platform economy, the main motivation for the adoption of precautionary measures, are not well-proven (specially with robust, empirical analysis), as discussed earlier in Chapter III.

Precautionary measures are one pillar of merger reviews and control, but, as it was mentioned before, it was used relatively rarely in the United States (e.g., per se rules against price fixing). Thus, the present discussion is adding new dimensions. An example are measures discussed by U.S. Congress to limit the ability of incumbent intermediation platforms to acquire nascent, technology companies, as the legislative proposals H.R.3816 – *American Choice and Innovation Online Act*, under discussion in the U.S. House of Representatives, and the S.2992 – *American Innovation and Choice Online Act*, under discussion in the U.S. Senate (U.S. House of Representatives, 2021; U.S. Senate, 2021).

These initiatives are based on allegations that the start-up acquisitions of incumbent platforms have the purpose of killing potential competitors. Strategic acquisitions are seen as harming venture capital investment and the digital innovation ecosystem overall. The referred legislative measures received strong opposition from venture capitalists. From their vantage point, prospective start-up acquisitions by incumbent platforms have been important positive incentives for venture investment and entrepreneurship in the United States (NVCA, 2021a; NVCA, 2021b). In Chapter III we have shown evidence consistent with these claims. Dippon and Hoelle (2022) offer a deeper analysis of the ex ante competition policy remedies targeting big tech platforms proposed in the U.S. Congress.

Khan (2017) had argued also that a revision of competition law is needed to empower antitrust agencies with newer, more agile, and effective tools to combat pre-emptive acquisitions and other competitive misconduct of incumbent digital platforms. Some scholars argue that the lengthy competition policy battles fought against the big techs in the last decade in the United States and in the EU demonstrate the limitations of purely ex post, anti-trust remedies to protect competition in the platform economy (Wheeler at al., 2020). These authors argue that ex post antitrust remedies, although welcome, are not fast enough to secure competition in extremely dynamic digital markets. Therefore, antitrust enforcement would become more effective with additional, ex ante remedies that can discourage competitive misconduct by incumbent platforms with market power.

Traditionally, interventions based on competition law are triggered not by market power per se, but by evidence of its abuse. As already mentioned in Chapter III, Professor Erik Hovenkamp, one of the panelists at the U.S. Department of Justice (2020) conference, eloquently explained that difficulties to compete against big tech do not constitute a competition policy problem. Thus, the existence of network effects as well as data and artificial intelligence (AI) capabilities, are not a sufficient cause for antitrust intervention. At the same time, the focus of the U.S. merger framework on short-run price effects after an acquisition is a shortcoming in digital markets. Very little is expected to happen immediately after the acquisition of a start-up by a big tech because the start-up is still too small. Instead, Professor Hovenkamp argued, the impact may appear in the long run and materialize, for example, in lower levels of innovation and investment. The current merger framework pays too little attention to these longer run factors.

The adoption of competition policy remedies to mitigate potential negative effects from big tech start-up acquisitions on long run innovation is highly controversial. It is likely that some start-up acquisitions seek to pre-empt competition for services offered by the incumbent platform. Others are likely motivated by obtaining access to complementary knowhow and technical staff. However, the ex ante definition of objective criteria to delineate the two, especially in markets with high rates of innovation, is afflicted with problems of asymmetric information and high uncertainty (Katz and Shelanski, 2007). Thus, it will be difficult to decide whether an acquired start-up would have had the means to challenge an incumbent platform in the long run.

Current antitrust practice in the United States and in Europe requires that antitrust authorities provide evidence of harm to competition and/or welfare generated by a big tech merger or acquisition. If harm is found, the big tech (defendant) can rebut the findings with evidence of welfare benefits. This approach, which is typically differentiated for horizontal and vertical mergers, allows assessment of the pros and const of a transaction. However, information to substantiate claims is often difficult to obtain and is often controlled by the big tech companies. To overcome this asymmetry, several authors have suggested to reverse the burden of proof if incumbent digital platforms are involved (e.g., Scott-Morton et al., 2019; Crémer et al., 2019).

In this policy design, an incumbent platform would have to provide evidence to support that the acquisition will not harm innovation and consumer welfare in the short and long run. This evidence is rebuttable by competition authorities. Motta and Peitz (2021) point out that changes in the notification thresholds, and of the tools currently available to stop such mergers would be required before such an approach could be implemented. For example, due to the complexity and lack of transparency in very dynamic digital markets, they propose the reversion of the burden of proof in merger reviews that involve incumbent digital platforms. Instead of requiring that antitrust authorities provide enough evidence of the harm of a big tech start-up acquisition, the incumbent digital platform is the one who would be obligated to provide supportive evidence that the acquisition will not harm innovation and consumer welfare in the short and long run.

Although reversing the burden of proof has certain appealing features, it also has shortcomings. For example, a one-sided assessment based on claims of benefits by the merging parties forgoes the full assessment of pros and cons of a merger at the heart of current practice (e.g., Hovenkamp and Shapiro, 2018). Also, the challenges of assessing market power in digital platform markets poses further challenges for the definition of clear, well-supported criteria to delineate situations where a reversed burden of proof should be used. Cabral (2021) presents additional critiques to this proposal. First, the author claims that the shift in the burden of proof would not be as efficient to overcome the complexity of the merger reviews than a strategy that would better equip antitrust enforcers to provide evidence of the harm of a big tech start-up acquisition. Second, he explains that such measures would impose difficulties to start-up acquisitions, with harmful impacts to the incentives for venture capital investments in nascent start-ups and consequently to the innovation ecosystem (especially in the United States). Finally, a bigger question arises on whether it is reasonable to modify rules of evidence just for a subset of competition cases in a subset of industries.

Further-reaching proposals for reforming the merger framework have been made, that would introduce a simple, precautionary blanket prohibition of big tech start-up acquisitions. The rationale is that, by preventing incumbent digital platforms from protecting their dominant positions through the incorporation or the killing of nascent competitors, they would have more incentives to invest in sustained innovating or risk being replaced by competitors at some point in the future. Also, other firms would have more incentives to invest in disruptive innovations, aiming at replacing the incumbent platforms.

There are at least two serious drawbacks of banning big tech, start-up acquisitions. First, Cabral (2021) argues that making start-up acquisitions more difficult would harm the innovation ecosystem, because, as already discussed in Chapter III, big tech start-up acquisitions fuel venture capital investment in the short-term and are an important exit strategy to venture capitalists. A blanket ban of big tech start-up acquisitions would increase the risk and lower profit prospects of venture investment, as it would reduce the chances of a VC investor successfully selling a start-up for a profit. Lower levels of VC investment may also discourage entrepreneurship and start-up creation, with negative impacts to consumer welfare (Lerner and Nanda, 2020).

Second, it would prevent legitimate, welfare-enhancing acquisitions motivated by the expectation of profit increase. In this case, not only would the incumbent platforms be unable to profit from the integration of complementary innovations, but a wide range of consumers (end users and small firms) would be prevented from accruing the positives effects of many innovations in the long run, as most start-ups fail to scale-up their innovations (U.S. Department of Justice, 2020).

These arguments suggest looking for a means other than broad prohibitions on acquisitions that can safeguard competition in the digital ecosystem. Gilbert (2021) suggests the consideration of a mix of antitrust enforcement and regulatory measures. For example, interoperability and data portability regulatory measures could be easily implemented - even by small start-ups. This would create means for more start-ups to develop killer, disruptive, innovative solutions that compete against big, incumbent players. In fact, well-funded start-ups with access to data and great AI tools should have good chances to succeed. They would ensure that the digital economy continues to generate high and long-lasting levels of investments and innovation to support economic development and welfare increases.

Ex post competition policy

Ex post, competition policy remedies serve the objective of fostering competition for the incumbent digital platforms but are only activated after concrete cases of abuse have materialized. They are set under the assumption that concentration is not necessarily welfare diminishing, as direct and indirect network effects as well as economies of scale and scope generate benefits to consumers and suppliers that use the intermediation platform. The rationale is that a concentrated market structure could be tolerated as long as competition policy enforcers can quickly identify and implement remedies in concrete cases of abusive conduct by incumbent platforms with market power.

Many scholars have pointed out that new, more flexible, and effective, competition policy would strengthen the current framework of competition policy in the United States and Europe (Shapiro, 2021). For example, Khan (2017) argues that the current competition policy framework is too narrowly construed. It focuses only on anticipated, short-term impacts of mergers and acquisitions on consumer welfare, assessed by the impacts on prices and total output. To overcome these shortcomings, a broader analytical framework is recommended, including the assessment of effects on competitors. Scott-Morton and Kades (2021) propose creating instruments that can be quickly invoked by competition policy authorities and implemented by incumbent platforms, such as standardized interoperability and data portability remedies to be imposed in cases of actionable competitive misconduct and abuse of market power.

Less intrusive and constraining, ex post alternatives to the blanket prohibition of acquisitions or a reversal of the burden of proof for all start-up acquisitions are also proposed. They overcome problems of asymmetric information and uncertainty and hence reduce the risk that acquisitions aimed at preempting competition are erroneously permitted. This can be achieved by reforms to the current merger framework that better distinguish between acquisitions that have positive effects from those that have negative ones. For example, Katz (2019) supports a shift in the burden of proof in merger reviews, but only in the cases where the plaintiff can show harm to the competitive process and harms to one or more user groups.

The research literature has generated several other proposals of ex post measures to enhance the current merger framework. For example, Scott-Morton et al. (2019) questions the capacity of generalist judges to deal with complex, conduct remedies and enforcement mechanisms required to address the abuse of market power by digital platforms. The authors then propose the establishment of a specialized antitrust court in the United States, which would decide cases involving digital platforms and, over the years, accumulate expertise that would allow a faster pace for merger reviews. For example, such courts could effectively deploy the standardized interoperability and data portability remedies mentioned above.

Complementing these arguments, Federico et al. (2020) argue that the main challenge for competition policy enforcers to develop a theory of harm in cases where an incumbent digital platform seeks to acquire a nascent, disruptive start-up is evidentiary. The authors explain that this happens because the start-up’s product, in most cases, is not a close substitute for the product of the incumbent platform and it may never develop into one. For example, when Facebook acquired Instagram, it would have been hard to establish that it was a threatening substitute to Facebook. The authors propose some useful methods to be adopted in merger reviews to lower the risk of under- and overenforcement under conditions of uncertainty.

To avoid underenforcement, the authors first suggest that the factors that determine the price of an acquisition should be carefully analyzed. The price and its determinants provide insights on whether the incumbent platform is either sharing monopoly rents with the owners of the acquired start-up (a "red flag"), or pricing a deal based on the present value of profit-maximizing, long-term synergies. Second, the authors suggest an analysis of past acquisitions of the incumbent platform seeking to acquire a nascent start-up. This would allow assessing whether the platform has a record of terminating acquired innovation projects or integrating them to enhance their products and services. Third, the nature of the acquired start-up, whether a substitute or a complement to the platform, is another good sign for the authors, as acquisitions of substitutes that may become a greater disruptive threat are more likely motivated by the goal of suppressing competition.

To mitigate overenforcement, Federico et al. (2020) suggest that competition policy authorities should assess the likelihood that the acquired start-up successfully brings its product to the market at scale, and the expected time that will take. The results of this assessment could be compared with the performance of the acquirer digital platform in achieving these outcomes in past acquisitions. Such measures would allow an error-cost assessment that increases the chances of antitrust enforcers blocking mergers aimed at pre-empting competition, without prohibiting those that are motivated by welfare-enhancing competition and innovation strategies.

Ex ante regulation

The adoption of ex ante regulatory measures may serve both the objectives of promoting competition for the platforms and fostering healthy and vigorous competition on the platforms. These measures are based on similar theoretical grounds as precautionary competition policy measures, and they generally aim at imposing safeguards to remedy anticipated harms of quasi-monopolist or oligopolist market structures. Some scholars point out that, while competition authorities can impose ex ante regulatory measures over incumbent platforms, the long-term oversight of regulatory interventions, especially those aimed to foster competition on the platforms, would require the establishment of a dedicated regulatory unit/department, equipped to gather specialized knowledge of the business of incumbent digital platforms and act faster than traditional competition policy enforcers (e.g., Scott-Morton et al., 2019; Wheeler et al., 2020).

Ex ante regulatory interventions to promote competition on the platform would be similar to utility-based economic regulation and would focus on managing anticipated consequences of inevitably concentrated digital markets (Dasgupta and Williams, 2020). Examples are the establishment of self-preferencing limits, privacy and customer care obligations, price caps to intermediation fees and to the insertion of advertisement content, among others. On the other hand, the fast-paced evolution of digital markets requires extensive analysis prior to the adoption of any of these ex ante measures, as it is hard to predict for how long their impact will remain positive (Frieden, 2018).

Examples of ex ante regulatory interventions aimed at fostering competition for the platform are the establishment of mandatory interoperability and data portability for digital platforms that hold market power in specific digital markets, as well as in-situ data access (Krämer, 2020; Scott-Morton and Kades, 2021, Van Alstyne et al., 2021). These proposed measures aim at reducing switching costs for stakeholders of both sides of the biggest digital platforms and foster entry of newcomers in the platform business. However, such measures should be taken after careful analysis of concrete market conditions. For example, Engels (2016) points out that data portability mandates would harm competition when platforms are substitutes, as it reduces the incumbents' incentives to invest. Also, Lam and Liu (2020) argue that such measures could encourage end users and suppliers to reveal even more information to incumbent platforms, with the prospect of carrying all their data to another platform whenever they want to. This side effect may increase data analytics network effects for incumbent platforms and consequently strengthen their dominant positions.

Many of these and other examples of ex ante regulatory measures are included in the recently approved European Union's Digital Markets Act – DMA (European Union Council, 2022). For example, Article 5, 6 and 7 of the DMA a selected group of big, U.S. digital platforms from tying different intermediation services provided by them in EU. They also outlaw combining platform data with personal data from other services offered by them or by affiliated third-party providers, unless an end user opts-in. Furthermore, the DMA obligates digital platforms to guarantee data portability, service interoperability, and the ability of end users to switch apps or services built-in on platform operating systems.

As happened with the GDPR, the DMA has the potential of shaping ex ante regulatory measures towards digital platforms around the world. Years after its adoption, the potential drawbacks to the digital economy of EU members brought by the GDPR are being assessed (Janssen et al., 2022). This suggests that a more careful analysis should be undertaken by policymakers of countries of other regions before importing remedies designed under the specific economic conditions of European countries.

Ex post regulation

Instead of anticipating potential harms to competition in the platforms due to the exercise of market power by incumbent platforms, as proposed by those who advocate for ex ante regulation, ex post approaches focus on responding to complaints and flagrant misconduct, and on the application of behavioral remedies to non-compliant platforms. The adoption of ex post regulatory oversight of incumbent platforms aims mainly at managing consequences of a concentrated market structure for competition *on* digital markets that run over any incumbent platforms. However, some ex post regulatory measures can also be adopted as a response to unfair conduct that reinforces market power of incumbent platforms and increases entry barriers into the platform intermediation business.

Examples of ex post regulatory measures to promote competition on the incumbent platforms are responses to limit potentially unfair sorting of offers in e-commerce platforms (e.g., the Google Shopping case in Europe). Such measures should avoid self-preferencing of platform's own retail business to the detriment of smaller retailers that rely on the platform to commercialize their products. On the other hand, Beard at al. (2022) explain that consumers, overwhelmed by an immense number of products offered online, benefit from some guidance. The authors also show that prohibitions to the establishment of criteria-based sorting, or imposition of randomized sorting are welfare-reducing.

Other examples of ex post, regulatory measures are related to responses to privacy breaches and mishandling of user's data. However, the effectiveness of measures, such as applying fines or the imposition of an obligation to include extra layers of consent forms to consumers, are questionable in light of research showing that the value of privacy to end users in many countries is low and may not affect consumer behavior strongly (Prince and Wallsten, 2022).

Also, to avoid that an incumbent's behavior reinforces its market position and creates restrictions that prevent other intermediation platforms from flourishing, some behavioral remedies may be imposed. Examples are remedies preventing platforms from refusing to interoperate with smaller platforms or preventing them from imposing non-compete clauses with their suppliers and employees. Also, data sharing obligations can be used as a regulatory measure to be taken against incumbent platforms in response to flagrant tentative of pre-emptying fair competition.

Finally, experts have argued that a specialized enforcement authority or appropriate capability within an existing agency would be required to enforce ex post regulatory remedies (Wheeler et al., 2020). Appropriately resourced, such an agency would be able to accumulate expertise in the analysis of different digital markets and follow the compliance history of incumbent intermediation platforms. A specialized regulator would add value by acting faster in case of abuses of market power than competition policy enforcers or the judiciary system, which may take years to reach a decision for this type of complaints (Scott-Morton at al., 2019).

The next section provides a scenario-based analysis of the alternative competition policy and regulatory regimes discussed in this Section and offers guidance on their likely effectiveness to promote competition *for* and *on* digital platforms in the presence of different microeconomic, institutional, and developmental conditions.

6.3. Alternative scenarios to promote competition in digital markets

With the adoption of new competition policy and regulatory measures by the European Union to promote competition *for* the platform business and *on* marketplaces created by the digital platforms, policymakers and regulators around the world might consider introducing similar measures. Divergent developmental trajectories of each political jurisdiction, however, might result in policy and regulatory regimes that vary in character and significance (Cioffi et al., 2022), as the simple copy of the European approach might not align with specific national conditions of the platform economy. The welfare enhancement and complementary innovations brought by incumbent digital platforms affect virtually all geographic markets where the digital platforms are offering their services. In search for appropriate policy responses, countries should weigh which competition policy and regulatory measures are best suited to the local scenario.

As already discussed in the last Section and in greater detail in Chapter II of this dissertation, concentration in digital markets is not seen as harmful by all research scholars. Rather, it has been contributing to digital inclusion and affordability of digital services that enhance productivity and promote socioeconomic development (e.g., search engines, web browsing, app stores, e-commerce). Also, the adoption of ex ante, pro-competitive measures will alter the incentives of incumbent digital platforms to sustain investment, innovation, and the provision of affordable digital services. It should, therefore, consider whether the economic and institutional conditions for entry in the platform intermediation business are present in the country or not.

Furthermore, the maturity of countries' or regions' innovation ecosystems and the size of the relevant consumer markets may constrain the likelihood that strong competitors to the incumbent digital platforms will emerge and find sustainable business opportunities. Success as a new entrant would require considerable scale (market size), expertise in the development of advanced data processing technologies (e.g., machine learning and deep learning algorithms, etc.), a large, specialized labor force (e.g., software and machine learning engineers, data scientists, etc.), and abundant venture investment for the complementary start-up ecosystem (as discussed in Chapter III of this dissertation).

Another dimension that should influence the adoption of a policy regime by a country are the capabilities of national institutions, for example to develop fine-tuned approaches, that may require fast responses, overarching economic analysis, and great enforcement power. Related literature for the telecommunications markets has shown that the institutional status quo affects what can be done and therefore is a constraining factor for the adoption of less rigid regimes (Levy and Spiller, 1996).

Moreover, the origin of incumbent platforms may influence the choice of policymakers for each regime, as the intermediation business ran by these platforms create key conditions for social and economic progress. For example, Cioffi et al. (2022) argue that the EU's DMA inaugurates an era of stringent regulatory interventions aimed at reasserting local societal interests more than competition itself. Therefore, the extent of the incumbent platforms' contribution to local socioeconomic conditions (e.g., to investment, innovation, employment, tax revenues, etc.) may influence policymakers towards promoting competition in the platform economy.

To contribute to the definition of balanced, effective country-specific platform regulation and competition policy remedies, it is necessary to consider the potential risks and benefits of the alternative measures reviewed in Section 6.2. To provide practical guidance on what policymakers must consider to tailor policy responses to their context, we describe four scenarios of countries based on the microeconomic, institutional, and developmental conditions as they relate to the digital economy.[31]

Then, we perform a qualitative, cost-benefit analysis, typical in the process of policy design, to assess the suitability of alternative pro-competitive regimes contingent on the relevant context of each country scenario. Table 6.1 summarizes the four scenarios, their dimensions, and proposed recommendations. These scenarios represent the most frequent, or prototypical, constellations of conditions encountered in countries around the world. In the following subsections we provide a detailed discussion of each scenario, the dimensions of analysis chosen, and the recommendations drawn.

It is important to note, however, that those scenarios are not intended to prescribe policy alternatives to be followed by each country. Specific approaches will require a comprehensive analysis of a country's geographic, political, socioeconomic, and institutional context. However, the scenarios provide a good starting-point to guide the policy debate, by illustrating the nature of the analysis and the types of tradeoffs that should be important to be carefully analyzed before one embarking in interventions aimed at promoting competition *for* and *on* incumbent digital platforms.

[31] The four scenarios cover most countries conditions, but those with weak institutional maturity with very different conditions that would exceed the purpose of this paper (e.g., lack of enforcement, or insufficient resources to develop market analysis).

Table 6.1 – Analysis of four country scenarios and potential interventions to promote competition for and in incumbent platforms

Scenarios	Adoption of Digital Services	Incumbent Digital Platforms	Market size (population)	Innovation ecosystem (level of development)	Availability of skilled tech workers	Institutional Maturity	Competition FOR the incumbent platforms	Competition ON the incumbent platforms
Scenario 1	High	Local	Big	High	High	Mature	• Large adoption of digital services has boosted productivity and economic growth. • Short term risks to contestability are diminished by the presence of other local big techs. • Ex ante competition policy remedies may cost innovation incentives of VCs and start-ups. • Ex post competition policy measures should help to keep digital markets contestable.	• Abusive terms in services provided by incumbents may be unlikely due to contestability. • Ex ante regulatory remedies have potential negative effects to innovation in the short-term. • Self/Co-regulation, and ex-post, agile measures to remedy misbehavior (e.g., unfair self-preferencing) should help keeping incentives to innovation and safeguard competition.
Scenario 2	High	Foreign	Big	High	High	Mature	• Capital accumulation, investments in innovation, and high-skilled jobs creation happen mainly in the countries of the incumbent digital platforms. • Contestability might regulate efficiency of dominant platforms, but policymakers may want to strengthen local platforms to increase countries total welfare. • Introduction of ex ante, competition policy remedies (to promote local entry), along with ex post measures (to keep contestability) might be appropriate.	• The mere expectation that contestability is sufficient to keep efficiency of the markets may not be enough to respond the need of local development. • The adoption of ex ante, regulatory remedies along with ex post measures should promote innovation, capital accumulation, and tech job creation locally. • In the long term, the costs to of this approach to innovation should be compared with its concrete benefits, to guarantee a positive net outcome.
Scenario 3	Moderate	Foreign or Local	Big	Moderate	Moderate	Moderate	• Policymakers should primarily aim at promoting the adoption of digital services, as well as the incentives for local incumbents to improve competitiveness. • For this set of objectives, ex ante competition policy may not be the right instrument. Rather, ex post, case-by-case analyses would bring a better balance. • Measures of market openness to foster the entry of foreign platforms should raise contestability and incentives for local incumbents to innovate.	• Given the dominance of local platforms with suboptimal services, ex ante regulation could be used to promote quality improvements and protect consumers (e.g., customer care, billing, privacy, etc.). • Ex post regulation should also protect platform users from unfair competition of the incumbent platforms, without creating high regulatory burden to an underdeveloped digital ecosystem.

Scenario 4	Low	Foreign	Big or Small	Low	Low	Moderate	• Policy should focus on increasing adoption for productivity growth, on building skilled tech workforce, as well as on promoting local innovation. • Ex ante competition policy remedies may negatively affect adoption, and entry of local players would depend on other microeconomic and institutional conditions. • Ex post competition policy might provide the right balance between increasing contestability without harming incentives for adoption and innovation.	• Ex ante regulatory measures could be designed to push foreign, incumbent platforms to contribute to the local innovation ecosystem and job creation. • Ex ante regulation focused on avoiding anticompetitive conduct should be weighed against their potential harms to affordability and adoption. • Ex post regulation should help remedying concrete cases of abuse of market power (e.g., unfair terms and conduct of incumbents, exclusionary agreements, self-preferencing, etc.).

Scenario 1

This scenario represents highly populated countries where digital services are widely adopted by people and businesses[32], there are domestic, dominant digital platforms, the innovation ecosystem is generative (start-up creation, patenting, and venture capital activity is intense), skilled tech workers are available, and competition policy and regulatory institutions are mature and stable.

Countries that meet such conditions are accruing considerable benefits of the platform economy. The broad adoption of digital services offered by incumbent platforms and other tech corporations have boosted productivity and economic growth throughout the economy. Investments in innovation, technology development, and high-skilled jobs creation have also been promoted locally by the domestic, incumbent platforms, generating long-term, socioeconomic development. In such scenarios, the potential risks associated with a concentrated market structure of digital markets are diminished by the presence of other local, big corporations with resources (funding, tech workers, tech infrastructure, etc.) to contest the dominance of incumbent platforms.

For countries of this scenario, instead of structural, ex ante competition policy remedies to promote entry in the platform business, at the cost of innovation incentives of incumbent platforms and other agents of the innovation ecosystem (venture capitalists, start-up founders, etc.), policymakers may primarily want to adopt measures aimed at safeguarding contestability. The risk of displacement by another powerful, tech corporation currently running in an adjacent market might be strong enough to regulate the behavior of incumbent

[32] For example, the International Digital Economy and Society Index (I-DESI), elaborated by the European Union, measure the development of the digital economy in five dimensions: connectivity, human capital, use of internet services, integration of digital technology, and digital public services (European Commission, 2022).

platforms towards maximizing efficiency in the allocation of inputs, as well as to the continued offer of affordable, innovative services to platform users. Improved and more agile, ex post competition policy measures can help keeping digital markets contestable by avoiding that the incumbent digital platforms abuse their market power to hinder the emergency of superior services.

It is reasonable to assume also that the imposition of abusive terms and conditions in digital services provided by incumbent platforms is unlikely in highly contestable markets. Therefore, the adoption of behavioral, ex ante regulatory remedies should be seen as suboptimal, due to their potential negative effects to innovation and to the emergency of alternative, yet unknown business models that may use the platform services to operate. Due to the maturity of competition policy and regulatory institutions, self or co-regulation, and ex post, fast-moving regulation that remedies misbehavior (e.g., unfair self-preferencing) will likely bring the right balance between supporting incentives to innovation and efficiency, while promoting competition in digital marketplaces controlled by incumbent platforms.

Scenario 2

Countries in Scenario 2 share some similarities with countries belonging to Scenario 1. This group represents populous countries in which digital services are widely adopted by individuals and businesses. Moreover, these countries have a strong innovation ecosystem, skilled tech workers, and mature and stable competition and regulatory institutions. However, due to technological advantages, the incumbent digital platforms are foreign corporations. The widespread adoption of platform services by the country's population and small businesses has generated productivity gains and long-term growth in several economic sectors. On the other hand, capital accumulation, investment in innovation and technology development, as well as high-skilled jobs creation happen mainly in the home country of the incumbent, foreign digital platforms.

Policymakers in this scenario probably are motivated to intervene in the market structure to promote the short-term emergence of national platforms that promise to promote innovation, capital accumulation, tax collection, and tech job creation locally. Moreover, they will likely be interested in supporting the conditions under which local complementors get access to platform innovation systems and services. The adoption of ex ante competition policy and regulatory remedies to more actively promoting entry of local players in the platform business, and reducing switching costs to end users should be weighed vis-à-vis the short-term costs to innovation and efficiency, already documented in the research literature and discussed in Section 6.2. In the long term, the costs created by this more stringent approach must be compared with the concrete benefits of such measures (e.g., local platform creation), to increase the likelihood that only measures with a long-run, positive net outcome are retained.

In addition, more effective and agile ex post competition policy remedies and court procedures that empower competition authorities and judges to decide quickly on cases of anticompetitive misconduct will likely help keeping markets contestable. However, contestability itself may not be sufficient to prevent incumbent, foreign platforms from an abuse of their intermediation position on their own digital marketplaces. Also, in these markets, anticompetitive conduct is hard to detect, and while investigations are pending, rents could be extracted from local businesses (platform users) and used to promote innovation and investment in the home country of the incumbent platform. The adoption of ex ante, regulatory remedies along with ex post measures to foster competition on the platforms might help to protect the local economy in the short-term against such risks. A softer intervention as proposed for countries of Scenario 1 may not provide equivalent safeguards.

Scenario 3

Countries described by this scenario are highly populated but with a moderate adoption of digital services among people and businesses. Innovation activity is moderate, much lower than in Scenario 1 and 2 countries, and skilled tech workers are in short supply. Competition and regulatory institutions are well-stablished, although their capacities and budget may be constrained and frequently affected by political and economic instability. Incumbent digital platforms are either local or foreign corporations, depending on each digital market, although local platforms frequently offer less innovative services when compared to foreign ones.

Countries in this scenario have neither accrued extensive gains from increased productivity and economic growth driven by a wide adoption of digital services (especially among small businesses), nor the extensive capital accumulation and technological progress seen in Scenario 1 and 2 countries. Therefore, policymakers should primarily aim at promoting the adoption of digital services, as well as providing market-based incentives for local incumbents to invest in process and product innovation to improve their ability to compete against potentially incoming foreign digital platforms.

For this set of objectives, ex ante competition policy may not be the right instrument. Rather, ex post, traditional case-by-case analyses would constitute the right balance. The focus should be on promoting affordability, digital inclusion, digital skills, and, frequently, connectivity infrastructure. Measures of market openness to foster the entry of foreign platforms, combined with incentives for them to build local data centers, innovation centers, tech-related jobs, etc., should raise contestability and provide incentives for local incumbents to keep innovating and investing.

The dominance of local platforms in some markets of these countries is fragile, as foreign players with superior technology and capital availability are soon expected to enter, attracted by the big market size. The risk of displacement should offer strong incentives for local, incumbent platforms to improve their efficiency. Therefore, instead of engaging in special ex ante competition policy regimes that may limit the ability of local platforms to strengthen themselves for competition against international players, policymakers might want to focus on fostering adoption of digital services and promoting the country's innovation ecosystem. Furthermore, the adoption of remedies that apply only to foreign platforms may be challenged in the courts as unfair national protectionism, while it may not contribute to provide the right incentives to local platforms keep investing in innovation and providing efficient services.

Where competition and contestability are insufficient, and platforms that offer suboptimal digital services are dominant, agile, well-designed ex ante regulation could be used to promote quality improvements and protect consumers from platform inefficiencies (e.g., customer care, billing, privacy, etc.). Ex post regulation should also be important to protect platform users from unfair competition on the platforms coming from the incumbent platforms themselves (e.g., self-preferencing), without creating too much regulatory burden to an underdeveloped digital ecosystem.

Scenario 4

Countries described by this scenario are characterized by a low penetration of digital services among people and businesses, even though they may be big or small economies. Maturity of competition and regulatory institutions is moderate as in countries of Scenario 3. Innovation activity is low, skilled tech workers are lacking, and incumbent digital platforms are foreign corporations.

These countries neither have accrued all the benefits of widespread use of digital services for enhancing productivity in the economy, nor have they benefited from the rise of local platforms and the associated local capital accumulation, investment in innovation and technology infrastructure, and tech job creation. To step up, policy should focus on increasing adoption of digital services for productivity growth, on promoting significant increases of skilled tech workforce, as well as on fostering local innovation and venture investment. Such conditions would create a proper environment for the birth of local platforms that may compete against foreign incumbents, as well as explore other markets and niches of the underdeveloped, local digital ecosystem.

Ex ante competition policies measures to raise means for local players to compete against foreign, platform incumbents would not be the first choice in this scenario. First, because these measures may create costs and inefficiencies that may negatively affect adoption of digital services currently provided by incumbent platforms. Second, because entry of local players would depend on conditions that are hard to alter in the short-term, like the availability of venture investment and skilled tech workers, an attractive environment for start-up entrepreneurship, among other conditions. Therefore, ex post competition policy remedies should provide the right balance between the need of increasing contestability and entry in the platform business, without harming incentives for adoption of digital services and investment in innovation activities of foreign incumbents.

Ex ante regulatory measures, on the other hand, could be designed to provide incentives for foreign, incumbent platforms to contribute to the local innovation ecosystem, as well as to promote local tech job creation. On the other hand, the adoption of ex ante regulatory remedies focused on avoiding anticompetitive conduct of incumbents in their marketplaces should be carefully weighed against their potential harms to affordability and adoption of digital services by the population and small businesses. In this scenario, ex post regulatory remedies might be well-measured to address concrete cases of abuse of market power (e.g., unfair terms and conduct of incumbents, exclusionary agreements, self-preferencing, etc.).

6.4. Competition policy and regulation implementation challenges

The task of creating policy and regulatory measures to promote competition in markets dominated by very influential and powerful incumbents is not new for governmental authorities in many countries. Competition policy and regulatory authorities have been dealing with lobbying and agency endeavors of big corporations in several economic sectors, like telecommunications, mass media, air transportation, oil and gas, banking, among others. Resourceful companies spend millions of dollars every year hiring consulting and advocacy firms to influence political and technical decisions of governmental authorities towards their private interests.

Setting new competition policy and regulatory rules in digital markets is already triggering similar reactions from incumbent digital platforms. Wheeler et al. (2020) point out that incumbent platforms have successfully convinced policymakers for several years that governmental oversight would harm their capacity to innovate. As a result, the authors say, three decades after the creation of the Internet, governmental agencies have only a limited understanding of the complex business models adopted by most digital companies. The exponential, fast-paced evolution of data accumulation and processing technologies, frequently based on proprietary algorithms, exacerbates information asymmetries between regulators and incumbent digital platforms.

This heightened information disparities, associated with the lack of a stablished culture of governmental oversight over digital markets (even for understanding their business models), are the main challenges faced by competition policy and regulatory authorities to adopt any of the five policy and regulatory alternatives discussed in Section 6.2. As a first step towards overcoming these challenges, Scott-Morton et al. (2019) propose the establishment of a specialized antitrust court, that would judge many cases involving digital platforms over the years and so accumulate some expertise on the topic.

Also, the creation of a specialized regulatory authority, or the empowerment of current regulatory authorities should be considered. It could be charged to oversight digital markets, produce studies and critical mass regarding their main business models, as well as adopt suitable ex post regulatory measures. Over the time, this would help reducing information asymmetries that currently undermine the credibility of governmental efforts to promote competition for the platforms and in the platforms.

Another important challenge to the effectiveness of competition policy and regulatory measures to the platform economy is the bounded rationality of the market agents of both sides of the digital platforms. The mainstream economic theory behind the adoption of competition policy and regulatory measures over platform intermediaries assumes that agents have infinite cognitive abilities and willpower to make the best decisions for themselves, without falling tempted by transitory benefits or altruism (Thaler, 2016). However, as the whole discipline of behavioral economics points, more favorable market conditions per se only provide incentives for users and suppliers switching, but they cannot force them to do so (Mullainathan and Thaler, 2000).

On this topic, Scott-Morton et al. (2019) recognizes that platform consumers have bounded rationality, what may create challenges for the success of policy interventions. For example, consumers are most likely to use the default apps pre-installed in their smartphones, access only the first search results they are shown, and incautiously agree with terms and conditions that allow platforms to collect, process, and extensively use their private information. According to the same authors, consumers make these non-rational decisions because of inherent behavioral biases, such as discounting the future too much and being too optimistic. Such behavioral attributes of internet users aid in diminishing the efficacy of competition policy and regulatory measures in the digital economy.

Finally, as discussed above, it is important to recognize that policymakers and regulators are also affected by bounded rationality when choosing the right regimes to safeguard competition *for* and *on* digital platforms. For example, they may discount too much potential long-term effects on innovation resultant from the adoption of ex ante remedies, or even they may not be able to envisage short-term effects of promoting competition to platform intermediates that are offering very good digital services to the society. These limitations are constraining the choices for the proper policy and regulatory regimes should have consequences to the development of digital markets, as well as for the innovation ecosystem.

For example, an overenforcement on incumbent digital platforms may result in price increases and less adoption of digital services in countries of scenarios 3 and 4, while the lack of enforcement may promote even more market power of local, inefficient incumbent platforms.

Therefore, policy also must undertake measures to reduce the risk of implementing wrong policy regimes overall. Safeguards could by created by adopting well-defined, agile cycles of re-assessment of the costs and benefits generated by the policies and regulations aimed at safeguarding competition in digital markets (OECD, 2021). However, policymakers and regulators eager for adopting agile and periodic assessment frameworks should define a comprehensive evaluation strategy and be equipped with appropriate resources and capabilities (e.g., data analytics, market intelligence division, curated and updated databases, etc.).

6.5. Main takeaways

This Chapter analyzed the appropriateness and efficiency of alternative competition policy and regulatory regimes proposed to promote competition in digital markets. We reviewed the complementary objectives of promoting competition *on*, and *for* incumbent digital platforms, and compared five different policy and regulatory approaches that are currently suggested in the research literature and explored by practitioners to achieve these two objectives. Finally, we have discussed the effectiveness and implementation challenges of these five alternative approaches in four prototypical scenarios of countries characterized by different socioeconomic, innovation, and market conditions.

A main conclusion is that carefully designed, fit-for-purpose competition policy and regulatory regimes, which observe country-specific conditions and challenges, are key to effectively promote competition without harming incentives for innovation and investment in the development of their digital ecosystem. A potential shortcoming of such a customized approach for promoting competition in digital markets is the risk that policy fragmentation around the world could impose excessive burdens on multi-national companies, impacting business plans, prices, and quality of digital services. On the other hand, such a risk already exists in competition policy and regulatory frameworks targeting brick-and-mortar markets, and it is mitigated by international coordination among antitrust, and regulatory enforcers (e.g., the UN's International Telecommunications Union - ITU, the World Trade Organization – WTO, etc.).

Our analysis supports a very limited use of ex ante, competition policy remedies to boost competition for the incumbent digital platforms, as the effectiveness of such approach to promote entry of new players is very dependent on exogenous conditions, like the existence of a robust innovation ecosystem, with abundant venture capital and skilled workforce, besides of a well-developed digital ecosystem. Reformed, ex post competition policy remedies might provide a better balance between raising contestability in concentrated, digital markets, and keeping incentives for incumbents invest in innovation and efficiency.

Furthermore, ex post regulatory regimes are recommended in all scenarios to remedy concrete cases of misbehavior and anticompetitive conduct of incumbent digital platforms in their own marketplaces, as well as to correct inefficiencies of scenarios with absence of imminent entry. Finally, ex ante, regulatory regimes might also serve to safeguard competition in digital marketplaces controlled by platforms, and they can also be used to promote local innovation and development in scenarios where incumbent platforms are foreign big techs.

Through this analysis, policymakers around the world can find guidance on what to consider when designing their policies to promote competition in digital markets. They can also understand what competition policy and regulatory regimes have been proposed by the research literature, as well as how to carefully weigh the effectiveness of each one given the countries' local conditions and challenges.

CHAPTER VII – CONCLUDING REMARKS AND FUTURE WORK

This dissertation made several original contributions to the research literature on platform economics. Building on recent developments in applied industrial organization theory, regulatory economics, and econometric methods, it expands the knowledge frontier in three, interrelated topics: i) the potential harms to innovation and investment resulting from the incumbency advantages accrued by big digital platforms, ii) the market power assessment in digital markets, and iii) how competition can be promoted in digital markets through alternative policy and regulatory regimes. Most chapters of this dissertation are self-contained, but they generate additional insights if considered together.

A first contribution that this dissertation provides is the theoretical and empirical investigation of the potential harms created by digital platforms for dynamic efficiency of digital markets. The chapter looks specifically at the repercussions of big-tech start-up acquisitions on the incentives for innovation in digital markets. It uses a unique data set of venture capital, IPO, and M&A activity between 2010 and 2020. A second contribution is the development of a conceptual framework for the assessment of market power in situations when large digital platforms are present in several, interrelated digital markets. This scenario poses several challenges to traditional methods of market power assessment, which typically rely on market-specific approaches.

A third contribution is the design and implementation of a theoretically and methodologically robust, empirical path for policymakers and competition authorities investigating the channels through which big digital platforms may exploit their market power. A survey, experimental research design was used to assess the relationship between online video platforms size and multi-market presence, and the tolerance of their users to digital ads and data collection procedures. A fourth contribution is the comparative analysis of different policy and regulatory regimes aimed at promoting competition in digital markets. These policies aim at promoting competition on markets served by dominant digital platforms and/or promoting competition for the dominant digital platforms. Of particular interest were the implications of alternative approaches on the alignment the objectives and likely outcomes.

The analysis of the effects of big tech start-up acquisition on funding for innovation suggested that a closer review of these mergers by better-equipped competition policy enforcers should be beneficial to deal with the complexities of digital markets. On the other hand, the findings of the empirical analysis of hundreds of big tech start-up acquisitions challenged claims about the existence of measurable, short-term, negative effects on venture capital funding for innovation by start-up firms. Rather, venture capital investment increased in average after the acquisitions analyzed, what suggest that, although new competition policy instruments may be needed to deal with mergers in the digital ecosystem, strict ex ante remedies may not bring the right incentives to promote digital innovation.

The proposed conceptual framework for market power assessment revealed the weaknesses of the prevailing approaches to market power analysis, which pay too little attention to multi-market presence. The conceptual analysis showed that when the digital service or product is offered free of charge for end users - a common scenario in digital markets - modified versions of the SSNIP test should be used to analyze the response of the users to different levels of digital ads and data collection procedures bundled with digital services. For supplier-side markets, the analyses showed that the SSNIP test applies, but that other tests are also needed to assess the response of advertisers and publishers to variations in the amount and variety of internet users' data owned by the supplying platform, and in the platform's market-shares in user-side, digital markets. Another conclusion is that effective remedies to promoting competition in multi-sided digital markets should be enforced jointly in both user- and supplier sides of the platforms.

To examine some of the assumptions of the theoretical analysis, an online survey experiment was conducted. It was designed to investigate the assumptions of the market power assessment framework allowed us to show that platforms benefit from their size and multi-market presence. The results suggest that a high market-share, and multi-market presence, make end users more tolerant to digital advertisements and data collection procedures embedded in most of their digital services. This frees large multi-market platforms to embed an above-equilibrium level of digital ads and data collection procedures in their services.

On one hand, this may reduce the utility that the end users could attain in a competitive scenario. It should also represent a competitive advantage for incumbent big techs, as it would reduce the likelihood that their end users switch to smaller competitors even when those offer services with less ads and data collection (two well-known sources of disutility for end users). On the other hand, these results may also suggest that concentration in some digital markets is welfare-enhancing, as these sources of disutility would generate less harm to the welfare of end users if the market is dominated by a big, multi-market incumbent platform, than if it is served equally by several platforms under perfect competition.

The analysis of alternative proposals of competition policy and regulatory regimes applied to digital markets examined their likely outcomes to promote competition *on,* and *for* the platforms in different country scenarios. Findings suggest that carefully designed, fit-for-purpose remedies are key to effectively promote competition without harming incentives for innovation and investment. Although nationally differentiated approaches may create policy fragmentation around the world, such a risk already exists in competition policy and regulatory frameworks targeting off-line markets, and it is commonly mitigated by international coordination.

The analysis concludes that reformed, ex post interventions might provide a better balance between raising contestability in concentrated, digital markets, and keeping incentives for incumbents invest in innovation and efficiency. Furthermore, we argue that ex post regulatory regimes are widely recommended to remedy concrete cases of anticompetitive conduct of incumbent digital platforms. Nonetheless, it also supports a very limited use of ex ante, competition policy remedies to boost local competition for incumbent digital platforms in countries with big internal market, a wide adoption of digital services, a well-developed innovation ecosystem, and an abundant tech labor supply. Ex ante, regulatory regimes might also serve to safeguard competition in digital marketplaces controlled by platforms, and they can also be used to promote local innovation and development in scenarios where incumbent platforms are foreign big techs.

The dissertation has deepened knowledge by developing theoretically and empirically grounded, novel contributions to three important current research areas and policy debates: the effect of big tech start-up acquisitions on incentives for innovation, the market power assessment in digital markets, and how policymakers and regulatory agencies can and should act to safeguard and promote competition in digital markets. It also helped explore the options policymakers have for the improvement of competition legal and regulatory frameworks. And, finally, it has explored ways to better orchestrate policy instruments with each other and with national and regional contexts.

Although this work has addressed a range of relevant topics that have advanced knowledge boundaries on platform economics and policy, several areas would benefit from additional research. For example, in the empirical analysis of effects of platform start-up acquisitions, aspects that deserve further investigation are potential spillover effects on industry segments adjacent to those selected by the big techs for the acquisitions. Also, data of start-up creations and their death rates could be investigated to figure out in which extent big techs' start-up acquisitions affect entrepreneurship and founders' willingness to create new start-ups in the same industry segment, as well as their chances for success after a big tech acquisition happens in their industry segment.

Furthermore, in the investigation of the influence of platforms size, and multi-market presence, on the nuisance costs of end users to digital ads and data collection procedures, further research should investigate such relationships with a wider set of platforms, to allow one controlling for a greater variety of characteristics of digital platforms. Also, future research may expand the experiment to investigate the relationship between the level of engagement of users with the platform in other markets, and their responses to digital ads and data privacy concerns for platforms other than Google, to allow further generalization of the results. In the same vein, although online video platforms are a common case set up to represent users' daily interactions with digital ads and data collection procedures, the investigation of these relationships in other ads-based services, like social media and search engines, for example, should contribute to allow generalizing our results to the entire digital economy.

Finally, in the analysis of alternative competition policy and regulatory remedies to prevent the exercise of market power by digital platforms, a topic for future research is the study of what institutional framework would be more suitable to foster competition in the digital economy without discouraging innovation and investments (e.g., a specialized regulatory authority, a traditional competition authority, or an empowered telecommunication regulatory authority). Also, it requires further investigation the extent to which national, pro-competitive measures towards digital markets would require international cooperation among competition authorities and regulators to be effective.

BIBLIOGRAPHY

Acquisti, A., and Spiekermann, S. (2011). Do interruptions pay off? Effects of interruptive ads on consumers' willingness to pay. Journal of Interactive Marketing, 25(4), 226-240.

Aghion, P., Antonin, C., and Bunel, S. (2021). The power of creative destruction. Harvard University Press.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., and Howitt, P. (2005). Competition and innovation: An inverted-U relationship. Quarterly Journal of Economics, 120(2), 701-728.

Armstrong, M. (2006). Competition in two-sided markets. The RAND Journal of Economics, 37(3), 668–691.

Armstrong, M., and Wright, J. (2007). Two-sided Markets, Competitive Bottlenecks and Exclusive Contracts. Economic Theory, 32(2), 353–380. https://doi.org/10.1007/s00199-006-0114-6.

Athey, S., and Imbens, G. W. (2021). Design-based analysis in difference-in-differences settings with staggered adoption. Journal of Econometrics, https://doi.org/10.1016/j.jeconom.2020.10.012.

Baek, T. H., and Morimoto, M. (2012). Stay away from me. Journal of advertising, 41(1), 59-76.

Baker, M., and Gompers, P. (2003). The determinants of board structure at the initial public offering. Journal of Law and Economics, 46(2), 569—98.

Bauer, J. M., & Knieps, G. (2018). Complementary innovation and network neutrality. Telecommunications Policy, 42(2), 172-183.

Baumol, W. J., Panzar, J. C., and Willig, R. D. (1982). Contestable Markets and the Theory of Industry Structure. Harcourt Brace Jovanovich.

Beard, R., Ford, G. S., and Stern, M. (2022). Product guidance by digital platforms: a welfare analysis. Phoenix Center Policy Bulleting No. 57. Available at https://www.phoenix center.org/PolicyBulletin/PCPB57Final.pdf.

Berry, S. T. (1994). Estimating Discrete-Choice Models of Product Differentiation. The RAND Journal of Economics, 25(2), 242. https://doi.org/10.2307/2555829

Berry, S., Levinsohn, J., and Pakes, A. (1995). Automobile prices in market equilibrium. Econometrica: Journal of the Econometric Society, 841-890.

Biglaiser, G., Crémer, J. and Veiga, A. (2022). Should I stay or should I go? Migrating away from an incumbent platform. The RAND Journal of Economics, 53: 453-483. https://doi.org/10.1111/1756-2171.12418

Bottazzi, L., and Da Rin, M. (2002). Venture capital in Europe and the financing of innovative companies. Economic Policy, 17(1), 229—69.

Bounie, D., Valérie, M., and Quinn, M. (2017). Do you see what I see? Ad viewability and the economics of online advertising. Ad Viewability and the Economics of Online Advertising. Available at https://www.lcii.eu/wp-content/uploads/2017/02/Bounie-Morrisson-Quinn-Ad-viewability-and-the-economics-of-online-advertising.pdf.

Bundeskartellamt (2019). Case Summary: Facebook, Exploitative business terms pursuant to Section 19(1) GWB for inadequate data processing. Bundeskartellamt. B6-22/16. Bonn. Germany. Retrieved on December 3, 2020, from https://www.bundeskartellamt.de/SharedDocs/Entscheidung/EN/Fallberichte/Missbrauchsaufsicht/2019/B6-22-16.pdf?__blob=publicationFile&v=4.

Byrne, E. (2018). Don't fear the big company 'kill zones,' TechCrunch. Retrieved June 4, 2021, from https://social.techcrunch.com/2018/08/07/dont-fear-the-big-company-kill-zones/.

Cabral, L. (2021). Merger policy in digital industries. Information Economics and Policy, 54, 100866. https://doi.org/10.1016/j.infoecopol.2020.100866

Caillaud, B. and Jullien, B. (2003). Chicken and Egg: Competition among Intermediation Service Providers. Rand Journal of Economics, pp. 309-328.

Callander, S., and Matouschek, N. (2021). The Novelty of Innovation: Competition, Disruption, and Antitrust Policy. Management Science, 68(1), 37-51.

Calvano, E., and Polo, M. (2021). Market power, competition and innovation in digital markets: A survey. Information Economics and Policy, 54, 100853. https://doi.org/10.1016/j.infoecopol.2020.100853.

Câmara dos Deputados do Brasil (2022). Projeto de Lei 2768/22. Dep. João Maia - PL/RN. Available at https://www.camara.leg.br/proposicoesWeb/fichadetramitacao?idProposicao=2337417

CB Insights (2021). Visualizing tech giants' billion-dollar acquisitions. February 24, 2021. Retrieved from https://www.cbinsights.com/research/tech-giants-billion-dollar-acquisitions-infographic/. Accessed April 30th, 2021.

Chaffee, S. H., and Metzger, M. J. (2001). The end of mass communication? Mass Communication & Society, 4(4), 365-379.

Cho, C.-H., and Cheon, H. J. (2004). Why Do People Avoid Advertising on the Internet? Journal of Advertising, 33(4), 89–97. https://doi.org/10.1080/00913367.2004.10639175

Cioffi, J. W., Kenney, M. F., and Zysman, J. (2022). Platform power and regulatory politics: Polanyi for the twenty-first century, New Political Economy, DOI: 10.1080/13563467.2022.2027355

Clark, J.M. (1940). Toward a concept of workable competition. American Economic Review, 30(2), 241-256.

Coate, M. B., and Fischer, J. H. (2008). A practical guide to the hypothetical monopolist test for market definition. Journal of Competition Law and Economics, 4(4), 1031–1063. https://doi.org/10.1093/joclec/nhn007

Crémer, J., Montjoye, Y.-A. de, Schweitzer, H. and Directorate-General for Competition - European Commission (2019). Competition policy for the digital era. Retrieved from http://publications.europa.eu/publication/manifestation_identifier/PUB_KD0419345ENN

Cunningham, C., Ederer, F., and Ma, S. (2021). Killer acquisitions. Journal of Political Economy, 129(3), 649-702.

Cusumano, M. A., Gawer, A., and Yoffie, D. B. (2019) The Business of Platforms: Strategy in the Age of Digital Competition, Innovation, and Power. Harper Business.

Cusumano, M. A., Yoffie, D. B., and Gawer, A. (2020). The future of platforms, MIT Sloan Management Review, Spring 2020, 46-54.

Cusumano, M., Gawer, A., and Yoffie, D. (2021). 'Can self-regulation save digital platforms?'. Under Review, Industrial and Corporate Change.

Da Rin, M., and Penas, M. F. (2007). The effect of venture capital on innovation strategies. Working paper No. w13636. National Bureau of Economic Research.

Da Rin, M., Hellmann, T., and Puri, M. (2013). A survey of venture capital research. In: G. Constantinides, M. Harris, and R. Stulz (eds.), Handbook of the Economics of Finance, Volume 2, Part A, 573–648. Amsterdam: Elsevier.

Dasgupta, K. and Williams, M. (2020). Competition Policy or Regulation: Does the History of Telecommunications Have Lessons for Platforms? ITS Europe Online event. June 2020.

De Corniere, A. and G. Taylor (2014). Integration and Search Engine Bias. Rand Journal of Economics, pp. 576-597.

Dippon, C. M., and Hoelle, M. D. (2022). The Economic Costs of Structural Separation, Line of Business Restrictions, and Common Carrier Regulation of Online Platforms and Marketplaces - A Quantitative Evaluation. NERA Economic Consulting. Washington, DC. Retrieved on August 17th, 2022, from https://www.nera.com/content/dam/nera/publications/2022/Platform_Regulation_Quantitative__03_18_22.pdf.

Duffett, R., Petroșanu, D. M., Negricea, I. C., and Edu, T. (2019). Effect of YouTube marketing communication on converting brand liking into preference among millennials regarding brands in general and sustainable offers in particular. Evidence from South Africa and Romania. Sustainability, 11(3), 604. https://doi.org/ 10.3390/su11030604

Dukes, A., and Gal–Or, E. (2003). Negotiations and exclusivity contracts for advertising. Marketing Science, 22(2), 222-245.

Engels, B. (2016). Data portability among online platforms. Internet Policy Review, 5(2).

European Commission (2017). Summary of Commission decision of 27 June 2017 relating to a proceeding under Article 102 of the Treaty on the Functioning of the European Union and Article 54 of the EEA Agreement (Case AT.39740 — Google Search (Shopping)). Official Journal of the European Union. 2018/C 9/08. Retrieved on December 3, 2020, from https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52018XC0112(01)&from=EN.

European Commission (2018a). Communication from the Commission: Guidelines on market analysis and the assessment of significant market power under the EU regulatory framework for electronic communications networks and services. Official Journal of the European Union. C 159. Retrieved from https://ec.europa.eu/digital-single-market/en/news/guidelines-market-analysis-and-assessment-significant-market-power.

European Commission (2018b). Commission Staff Working Document: Accompanying the document "Communication from the Commission: Guidelines on market analysis and the assessment of significant market power under the EU regulatory framework for electronic communications networks and services." SWD (2018) 124 final. Retrieved from https://ec.europa.eu/digital-single-market/en/news/guidelines-market-analysis-and-assessment-significant-market-power.

European Commission (2020). Digital Services Act package – ex ante regulatory instrument of very large online platforms acting as gatekeepers. European Commission. Law. Public Consultation. Brussels. Belgium. Retrieved on December 3, 2020, from https://ec.europa.eu/info/law/better-regulation/have-your-say/initiatives/12418-Digital-Services-Act-package-ex-ante-regulatory-instrument-of-very-large-online-platforms-acting-as-gatekeepers.

European Commission (2022). The Digital Economy and Society Index (DESI). Brussels. Belgium. Available at https://digital-strategy.ec.europa.eu/en/policies/desi

European Union Council (2022). Proposition de règlement du parlement européen et du conseil elative aux marchés contestables et équitables dans le secteur numérique (législation sur les marchés numériques). Secretary General of the Council. Brussels. Belgium. Retrieved from https://www.consilium.europa.eu/media/56086/st08722-xx22.pdf.

Ezrachi, A., and Stucke, M. E. (2016). Virtual competition: The promise and perils of the algorithm-driven economy. Cambridge, MA: Harvard University Press.

Ezrachi, A., and Stucke, M. E. (2022). How big-tech barons smash innovation—and how to strike back. Harper Business.

Fan, M., Kumar, S., and Whinston, A. B. (2007). Selling or Advertising: Strategies for Providing Digital Media Online. Journal of Management Information Systems, 24(3), 143–166. https://doi.org/10.2753/MIS0742-1222240305

Faria, A. P., and Barbosa, N. (2014). Does venture capital really foster innovation? Economics Letters, 122(2), 129-131.

Federico, G., Morton, F. S., and Shapiro, C. (2020). Antitrust and innovation: Welcoming and protecting disruption. Innovation Policy and the Economy, 20(1), 125-190.

Feeney, L., Haines JR, G. H., and Riding, A. L. (1999). Private investors' investment criteria: Insights from qualitative data. Venture Capital: An International Journal of Entrepreneurial Finance, 1(2), 121-145, DOI: 10.1080/136910699295938.

Flew, T., and Martin, F. R. (Eds.). (2022). Digital platform regulation: Global perspectives on Internet governance. Palgrave Macmillan.

Foerderer, J., Kude, T., Mithas, S., and Heinzl, A. (2018). Does platform owner's entry crowd out innovation? Evidence from Google Photos. Information Systems Research, 29(2), 444-460.

Frade, J. L. H., de Oliveira, J. H. C., & Giraldi, J. D. M. E. (2021). Advertising in streaming video: An integrative literature review and research agenda. Telecommunications Policy, 45(9), 102186.

Frieden, R. (2018). The Internet of Platforms and Two-Sided Markets: Implications for Competition and Consumers, 63 Villanova Law Review, 269. Available at: https://digitalcommons.law.villanova.edu/vlr/vol63/iss2/3.

Fumagalli, C., Motta, M., and Tarantino, E. (2022). Shelving or Developing? The Acquisition of Potential Competitors under Financial Constraints. CSEF Working Papers 637, Centre for Studies in Economics and Finance (CSEF), University of Naples, Italy.

Gautier, A., and Lamesch, J. (2021). Mergers in the digital economy. Information Economics and Policy, 54, 100890.

Gilbert, R. J. (2020). Innovation matters: competition policy for the high-technology economy. MIT Press.

Gilbert, R. J. (2021). Separation: A Cure for Abuse of Platform Dominance? Information Economics and Policy, 54, 100876. https://doi.org/10.1016/j.infoecopol.2020.100876.

Gillespie, T. (2018). Custodians of the Internet: Platforms, Content Moderation, and the Hidden Decisions That Shape Social Media. Yale University Press.

Gompers, P. A. (1996). Grandstanding in the venture capital industry. Journal of Financial Economics, 42(1). 133–156.

Gompers, P. A., and Lerner, J. (2001). The venture capital revolution. Journal of Economic Perspectives, 15(2), 145-168.

Gompers, P. A., and Lerner, J. (2004). The Venture Capital Cycle. Cambridge, MA: MIT Press.

Gompers, P. A., Gornall, W., Kaplan, S. N., and Strebulaev, I. A. (2020). How do venture capitalists make decisions? Journal of Financial Economics, 135(1), 169–90.

Goodman-Bacon, A. (2018). Difference-in-differences with variation in treatment timing. NBER Working Paper No. 25018. September 2018. Available at https://www.nber.org/system/files/working_papers/w25018/w25018.pdf.

Hagiu, A and J Wright (2015). Marketplace or reseller? Management Science 61(1): 184-203.

Haucap, J., and Heimeshoff, U. (2014). Google, Facebook, Amazon, eBay: Is the Internet driving competition or market monopolization? International Economics and Economic Policy, 11(1–2) 49–61. doi:10.1007/s10368-013-0247-6 https://doi.org/10.1016/j.infoecopol.2020.100865.

Hayek, F. A. (1949). The meaning of competition. In F. A. v. Hayek (Ed.), Individualism and economic order. Routledge.

Helmond, A. (2015). The Platformization of the Web: Making Web Data Platform Ready. Social Media + Society, 1(2), 205630511560308. Retrieved from https://doi.org/10.1177/2056305115603080.

Hirano, K., Imbens, G., Ridder, G. (2003). Efficient estimation of average treatment effects using the estimated propensity score. Econometrica, 71(4), 1307-1338.

Hovenkamp, H., and Shapiro, C. (2018). Horizontal mergers, market structure, and burdens of proof. The Yale Law Journal, 127(7), 1996-2025.

Imai, K., Kim, I. S., and Wang, E. (2021). Matching methods for causal inference with time-series cross-sectional data. American Journal of Political Science, https://doi.org/10.1111/ajps.12685.

International Telecommunications Union - ITU (2016). ITU-T Recommendation D.261: Regulatory principles for market definition and identification of operators with significant market power – SMP. Retrieved from https://www.itu.int/rec/T-REC-D.261-201610-I.

Janssen, R., Kesler, R., Kummer, M. E., and Waldfogel, J. (2022). GDPR and the lost generation of innovative apps (No. w30028). National Bureau of Economic Research.

Joa, C. Y., Kim, K., and Ha, L. (2018). What makes people watch online in-stream video advertisements? Journal of Interactive Advertising, 18(1), 1–14. https://doi.org/ 10.1080/15252019.2018.1437853

Johnson, L. (2022). Here's How much ads cost on Google, Meta, Amazon, TikTok, and Snap. Business Insider. Available at https://www.businessinsider.com/digital-ad-prices-are-skyrocketing-in-2022-2

Johnson, V. L., Kiser, A., Washington, R., and Torres, R. (2018). Limitations to the rapid adoption of M-payment services: Understanding the impact of privacy risk on M-Payment services. Computers in Human Behavior, 79, 111–122. https://doi.org/10.1016/j.chb.2017.10.035

Kamepalli, S. K., Rajan, R., and Zingales, L. (2020). Kill zone (No. w27146). National Bureau of Economic Research.

Katz, M. L. (2019). Platform economics and antitrust enforcement: A little knowledge is a dangerous thing: KATZ. Journal of Economics and Management Strategy, 28(1), 138–152. https://doi.org/10.1111/jems.12304.

Katz, M. L. (2021). Big Tech mergers: Innovation, competition for the market, and the acquisition of emerging competitors. Information Economics and Policy, 54, 100883. https://doi.org/10.1016/j.infoecopol.2020.100883

Katz, M. L., and Shelanski, H. A. (2007). Merger analysis and the treatment of uncertainty: Should we expect better? Antitrust Law Journal, 74(3), 537-574.

Kennedy, J. (2020). Monopoly myths: Is big tech creating "kill zones"? Information Technology and Innovation Foundation. Retrieved June 11, 2021, from https://itif.org/publications/2020/11/09/monopoly-myths-big-tech-creating-kill-zones.

Khan, L. (2017). Amazon's antitrust paradox. Yale Law Journal, 126(3), 710-805.

Kortum, S., and Lerner, J. (1998). Does venture capital spur innovation? Working paper No. w6846. National Bureau of Economic Research.

Kortum, S., and Lerner, J. (2000). Assessing the contribution of venture capital to innovation. RAND Journal of Economics, 31(4), 674-692.

Krämer, B. (2017). Populist online practices: the function of the Internet in right-wing populism, Information, Communication & Society, 20:9, 1293-1309, DOI: 10.1080/1369118X.2017.1328520.

Krämer, J. (2020). Personal Data Portability in The Platform Economy: Economic Implications and Policy Recommendations. Journal of Competition Law & Economics.

Kulick, R. (2021) The Economic Impact of Instacart on the U.S. Retail Grocery Industry Before and During the COVID-19 Pandemic. NERA Economic Consulting. Washington, DC. Available at https://www.nera.com/publications/archive/case-project-experience/nera-study-finds-direct-causal-relationship-between-instacart-ad.html

Laffont, J.-J., and Tirole, J. (1999). Competition in telecommunications. MIT Press.

Lam, W.M.W., Liu, X. (2020). Does data portability facilitate entry? International Journal of Industrial Organization, 69: 102564. https://doi.org/10.1016/j.ijindorg.2019.102564.

Lazarsfeld, P.F., and Merton, R. (1948). Mass communication popular taste and organized social action.

Lerner, A. P. (1934). The Concept of Monopoly and the Measurement of Monopoly Power. The Review of Economic Studies. 1 (3): 157–175. doi:10.2307/2967480.

Lerner, J. (1995). Venture capitalists and the oversight of private firms. Journal of Finance, 50(1), pp. 301–18.

Lerner, J., and Nanda, R. (2020). Venture capital's role in financing innovation: What we know and how much we still need to learn. Journal of Economic Perspectives, 34(3), 237-61.

Letina, I., Schmutzler, A., and Seibel, R. (2021). Killer acquisitions and beyond: Policy effects on innovation strategies. University of Zurich, Department of Economics, Working Paper. No. 358, revised version. Available at SSRN: https://ssrn.com/abstract=3673150.

Levy, B., and Spiller, P. T. (1996). Regulations, Institutions, and Commitments: Comparative Studies of Telecommunications. Cambridge University Press.

Loeb, W. (2021). The Rising Costs of Digital Advertising Will Force Spending Shifts. Forbes - Business - Retail. Available at https://www.forbes.com/sites/walterloeb/2021/08/04/rising-costs-of-digital-advertising-will-force-spending-shifts/?sh=2a2612245a7c

Logan, K. (2013). And now a word from our sponsor: Do consumers perceive advertising on traditional television and online streaming video differently? Journal of Marketing Communications, 19(4), 258–276. https://doi.org/10.1080/13527266.2011.631568

Mansell, R., and Steinmueller, W. E. (2020). Advanced introduction to platform economics. Edward Elgar Publishing.

Marsden, C. T. (2011). Internet co-regulation: European law, regulatory governance and legitimacy in cyberspace. Cambridge University Press.

Martin, K. (2018). The penalty for privacy violations: How privacy violations impact trust online. Journal of Business Research, 82, 103–116. https://doi.org/10.1016/j.jbusres.2017.08.034.

May, P. J., and Jochim, A. E. (2013). Policy regime perspectives: Policies, politics, and governing. Policy Studies Journal, 41(3), 426-452.

Motta, M., and Peitz, M. (2021). Big tech mergers. Information Economics and Policy, 54, 100868. https://doi.org/10.1016/j.infoecopol.2020.100868

Mullainathan, S., and Thaler, R. H. (2000). Behavioral economics (No. w7948). National Bureau of Economic Research.

National Venture Capital Association - NVCA (2021a). NVCA letter of opposition - Platform Competition and Accountability Act. June. Available at https://nvca.org/wp-content/uploads/2021/06/NVCA-letter-of-opposition-Platform-Competition-and-Accountability-Act.pdf

National Venture Capital Association - NVCA (2021b). Senate Antitrust Bill Hurts Innovation, Growth and Creation of New Innovative American Companies. November. Available at https://nvca.org/pressreleases/senate-antitrust-bill-hurts-innovation-growth-and-creation-of-new-innovative-american-companies/.

Nevo, A. (2000). A Practitioner's Guide to Estimation of Random-Coefficients Logit Models of Demand. Journal of Economics & Management Strategy, 9: 513-548. https://doi.org/10.1111/j.1430-9134.2000.00513.x.

OECD (1993). Glossary of industrial organization economics and competition law. Paris: Organization for Economic Co-operation and Development. Retrieved from http://www.oecd.org/regreform/sectors/2376087.pdf.

OECD. (2018). Oslo Manual 2018. The measurement of scientific, technological and innovation activities. Paris: Organisation for Economic Co-operation and Development.

OECD. (2021). Recommendation of the Council for Agile Regulatory Governance to Harness Innovation, OECD/LEGAL/0464. Paris: Organisation for Economic Co-operation and Development.

Owen, B. M., and Wildman, S. S. (1992). Video Economics. Cambridge, MA: Harvard University Press.

Pagani, M. (2013). Digital Business Strategy and Value Creation: Framing the Dynamic Cycle of Control Points. MIS Quarterly (37:2), pp. 617–632.

Papies, D., Eggers, F., and Wlömert, N. (2011). Music for free? How free ad-funded downloads affect consumer choice. Journal of the Academy of Marketing Science, 39(5), 777-794.

Parker, G., and Van Alstyne, M. (2017). “Innovation, Openness, and Platform Control,” Management Science (in Advance: October), pp. 1–18.

Petit, N. (2020). Big tech and the digital economy: The moligopoly scenario. Oxford University Press.

Petit, N., and Teece, D. J. (2021). Innovating big tech firms and competition policy: Favoring dynamic over static competition. Industrial and Corporate Change, 30(5), 1168-1198.

Prasad, A., Mahajan, V., and Bronnenberg, B. (2003). Advertising versus pay-per-view in electronic media. International Journal of Research in Marketing, 20(1), 13–30. https://doi.org/10.1016/S0167-8116(02)00119-2

Prat, A., and Valletti, T. (2022). Attention Oligopoly. American Economic Journal: Microeconomics, 14(3):530-57.

Prince, J. T., and Wallsten, S. (2022). How much is privacy worth around the world and across platforms? Journal of Economics & Management Strategy. https://doi.org/10.1111/jems.12481

Rochet, J.-C., and Tirole, J. (2003). Platform Competition in Two-Sided Markets. Journal of the European Economic Association, 1(4), 990–1029. https://doi.org/10.1162/154247603322493212.

Rolnik, Guy, Julia Cagé, Joshua Gans, Ellen Goodman, Brian Knight, Andrea Prat, Anya Schiffrin, and Prateek Raj (2019). "Protecting journalism in the age of digital platforms." Committee for the Study of Digital Platforms Media Subcommittee. Chicago: Stigler Center for the Study of the Economy and the State. University of Chicago Booth School of Business.

Rosen, J. (2011). The Deciders: The Future of Privacy and Free Speech in the Age of Facebook and Google. Fordham Law Review, 80, 1525.

Rosenbaum, P. R., and Rubin, D. B. (1983). Assessing sensitivity to an unobserved binary covariate in an observational study with binary outcome. Journal of the Royal Statistical Society, Series B (Methodological), 45(2), 212-218.

Rosse, J. N. (1970). Estimating cost function parameters without using cost data: Illustrated methodology. Econometrica, 38(2), 256-275.

Russell Neuman, W., Guggenheim, L., Mo Jang, S. A., & Bae, S. Y. (2014). The dynamics of public attention: Agenda-setting theory meets big data. Journal of communication, 64(2), 193-214.

Schumpeter, J. A. (1942). Capitalism, socialism, and democracy. Harper.

Scott-Morton, F. M., and Kades, M. (2021). Interoperability as a Competition Remedy for Digital Networks. Available at http://dx.doi.org/10.2139/ssrn.3808372.

Scott-Morton, F. M., Bouvier, P., Ezrachi, A., Jullien, B., Katz, R., Kimmelman, G. , Melamed, A. , Morgenstern, J. (2019). Committee for the Study of Digital Platforms: Market Structure and Antitrust Subcommittee - Report. Stigler Center for the Study of the Economy and the State, University of Chicago Booth School of Business, Chicago.

Shapiro, C. (2021). Antitrust: What Went Wrong and How to Fix It. American Bar Association. Antitrust, Vol. 35, No. 3, Summer.

Sørensen, M. (2007). How smart is smart money? A two-sided matching model of venture capital. The Journal of Finance, 62(6), 2725-2762.

Spagnoletti, P., Resca, A., and Lee, G. (2015). A design theory for digital platforms supporting online communities: a multiple case study. Journal of Information Technology (30:4), pp. 364–380.

Spulber, D. F. (2019). The economics of markets and platforms. Journal of Economics & Management Strategy, 28(1), 159-172.

Stocker, V., Knieps, G., and Dietzel, C. (2021). The rise and evolution of clouds and private networks–internet interconnection, ecosystem fragmentation (August 23, 2021). Available at SSRN: https://ssrn.com/abstract=3910108.

Strahilevitz, L., Cranor, L. F., Marotta-Wurgler, F., Mayer, J., Ohm, P., Strandburg, K., and Ur, B. (2019). Committee for the Study of Digital Platforms: Privacy and Data Protection Subcommittee - Report. Stigler Center for the Study of the Economy and the State, University of Chicago Booth School of Business, Chicago.

Strandburg, K. J. (2013). Free Fall: The Online Market's Consumer Preference Disconnect. University of Chicago Legal Forum: Vol. 2013, Article 5. Available at: http://chicagounbound.uchicago.edu/uclf/vol2013/iss1/5.

Tan, B., Pan, S. L., Lu, X., and Huang, L. (2015). The Role of IS Capabilities in the Development of Multi-Sided Platforms: The Digital Ecosystem Strategy of Alibaba.com. Journal of the Association for Information Systems (16:4), pp. 248–280.

Thaler, R. H. (2016). Behavioral economics: Past, present, and future. American Economic Review, 106(7), 1577-1600.

Tirole, J. (1988). The theory of industrial organization. MIT Press.

Tucker, C. E. (2012). The economics of advertising and privacy. International journal of Industrial organization, 30(3), 326-329.

U.K. Competition and Markets Authorithy (2020). Online platforms and digital advertising: Market study final report. Competition and Markets Authority. Retrieved on December 3, 2020, from https://www.gov.uk/cma-cases/online-platforms-and-digital-advertising-market-study#final-report.

U.K. Treasury, H. M. (2019). Unlocking digital competition, Report of the Digital Competition Expert Panel. Available at https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/785547/unlocking_digital_competition_furman_review_web.pdf

U.S. Department of Justice (2020). Public Workshop on Venture Capital and Antitrust. Antitrust Division. Washington, DC. Available at https://www.justice.gov/atr/events/public-workshop-venture-capital-and-antitrust.

U.S. Federal Trade Commission (2020). FTC to Examine Past Acquisitions by Large Technology Companies: Agency Issues 6(b) Orders to Alphabet Inc., Amazon.com, Inc., Apple Inc., Facebook, Inc., Google Inc., and Microsoft Corp. Federal Trade Commission: Press Releases. Washington, DC. Retrieved on December 3rd, 2020, from https://www.ftc.gov/news-events/press-releases/2020/02/ftc-examine-past-acquisitions-large-technology-companies.

U.S. House of Representatives (2021). H.R.3826 - Platform Competition and Opportunity Act of 2021. Committee: House – Judiciary. Available at https://www.congress.gov/bill/117th-congress/house-bill/3826/text.

U.S. Senate (2021). S.225 - Competition and Antitrust Law Enforcement Reform Act of 2021. Committee: Senate – Judiciary. Available at https://www.congress.gov/bill/117th-congress/senate-bill/225/text.

Vakratsas, D., and Ambler, T. (1999). How advertising works: what do we really know? Journal of marketing, 63(1), 26-43.

Van Alstyne, M. W., Petropoulos, G., Parker, G., and Martens, B. (2021). 'In situ' data rights. Communications of the ACM, 64(12), 34-35.

Van Dijck, J., Poell, T., and De Waal, M. (2018). The platform society: Public values in a connective world. Oxford, UK; New York: Oxford University Press.

Varian, H. R. (2021). Seven deadly sins of tech? Information Economics and Policy, 54, 100893. https://doi.org/10.1016/j.infoecopol.2020.100893

von Grafenstein, M. (2022). Co-regulation and competitive advantage in the GDPR: Data protection certification mechanisms, codes of conduct and data protection-by-design. Research Handbook on Privacy and Data Protection Law. Pages 402-432. Edward Elgar Publishing.

Wang, Y., and Herrando, C. (2019). Does privacy assurance on social commerce sites matter to millennials? International Journal of Information Management, 44, 164–177. https://doi.org/10.1016/j.ijinfomgt.2018.10.016

Wheeler, T., Verveer, P., and Kimmelman, G. (2020). New digital realities; new oversight solutions in the U.S. The case for a Digital Platform Agency and a new approach to regulatory oversight. Discussion Paper, Shorenstein Center on Media, Politics and Public Policy, Harvard University.

Wooldridge, J. M. (2010). Econometric analysis of cross section and panel data. Cambridge, MA: MIT press.

Wu, T. (2018). The curse of bigness: Antitrust in the new gilded age, New York: Columbia Global Reports.

Young, D., and McGregor, S. (2020). Mass propaganda used to be difficult, but Facebook made it easy: Americans want — and need — regulation of microtargeting now. The Washington Post. Made by History – Perspective.

Zhang, K., and Sarvary, M. (2015). Differentiation with user-generated content. Management Science, 61(4), 898-914.

APPENDIX I – List of Sector – Industry – Industry Segment

Sector	Industry	Industry Segment
Internet	Internet Soft. & Serv.	Accounting & Finance
Internet	Internet Soft. & Serv.	Advertising Network or Exchange
Internet	Internet Soft. & Serv.	Advertising, Sales & Marketing
Internet	Internet Soft. & Serv.	Apparel & Accessories
Internet	Internet Soft. & Serv.	Application & Data Integration
Internet	Internet Soft. & Serv.	Asset & Financial Management & Trading
Internet	Internet Soft. & Serv.	Auto
Internet	Internet Soft. & Serv.	B2B Commerce
Internet	Internet Soft. & Serv.	Billing, Expense Management and Procurement
Internet	Internet Soft. & Serv.	Browser Software/Plugins
Internet	Internet Soft. & Serv.	Business Intelligence, Analytics & Performance Mgmt
Internet	Internet Soft. & Serv.	Collaboration & Project Management
Internet	Internet Soft. & Serv.	Compliance
Internet	Internet Soft. & Serv.	Conferencing & Communication
Internet	Internet Soft. & Serv.	Content Management
Internet	Internet Soft. & Serv.	Customer Relationship Management
Internet	Internet Soft. & Serv.	Data & Broadband
Internet	Internet Soft. & Serv.	Data & Document Management
Internet	Internet Soft. & Serv.	Data Storage
Internet	Internet Soft. & Serv.	Database Management
Internet	Internet Soft. & Serv.	Domain & SEO Services
Internet	Internet Soft. & Serv.	Education & Training
Internet	Internet Soft. & Serv.	Email
Internet	Internet Soft. & Serv.	Food & Grocery
Internet	Internet Soft. & Serv.	Gambling
Internet	Internet Soft. & Serv.	Gaming
Internet	Internet Soft. & Serv.	Government
Internet	Internet Soft. & Serv.	Green/Environmental
Internet	Internet Soft. & Serv.	HR & Workforce Management
Internet	Internet Soft. & Serv.	Health & Wellness
Internet	Internet Soft. & Serv.	Healthcare
Internet	Internet Soft. & Serv.	Information Providers & Portals
Internet	Internet Soft. & Serv.	Internet Service Provider
Internet	Internet Soft. & Serv.	Legal
Internet	Internet Soft. & Serv.	Manufacturing, Warehousing & Industrial
Internet	Internet Soft. & Serv.	Marketplace
Internet	Internet Soft. & Serv.	Monitoring & Security
Internet	Internet Soft. & Serv.	Multi-Product
Internet	Internet Soft. & Serv.	Multimedia & Graphics
Internet	Internet Soft. & Serv.	Music
Internet	Internet Soft. & Serv.	Music, Video, Books & Entertainment

Sector	Industry	Subindustry
Internet	Internet Soft. & Serv.	Networking & Connectivity
Internet	Internet Soft. & Serv.	News & Discussion
Internet	Internet Soft. & Serv.	Operating Systems & Utility
Internet	Internet Soft. & Serv.	Payments
Internet	Internet Soft. & Serv.	Personal & Professional Development
Internet	Internet Soft. & Serv.	Photo
Internet	Internet Soft. & Serv.	Real Estate
Internet	Internet Soft. & Serv.	Retail & Inventory
Internet	Internet Soft. & Serv.	Scientific, Engineering
Internet	Internet Soft. & Serv.	Search
Internet	Internet Soft. & Serv.	Social
Internet	Internet Soft. & Serv.	Sporting Goods
Internet	Internet Soft. & Serv.	Sports
Internet	Internet Soft. & Serv.	Supply Chain & Logistics
Internet	Internet Soft. & Serv.	Testing
Internet	Internet Soft. & Serv.	Travel
Internet	Internet Soft. & Serv.	Video
Internet	Internet Soft. & Serv.	Web Development
Internet	Internet Soft. & Serv.	Website hosting
Internet	Internet Soft. & Serv.	eCommerce enablement
Internet	eCommerce	Accounting & Finance
Internet	eCommerce	Advertising, Sales & Marketing
Internet	eCommerce	Apparel & Accessories
Internet	eCommerce	Asset & Financial Management & Trading
Internet	eCommerce	Auction & Classifieds
Internet	eCommerce	Auto
Internet	eCommerce	B2B Commerce
Internet	eCommerce	Collaboration & Project Management
Internet	eCommerce	Comparison Shopping
Internet	eCommerce	Computer & Software
Internet	eCommerce	Digital Goods
Internet	eCommerce	Discount
Internet	eCommerce	Education & Training
Internet	eCommerce	Electronics & Appliances
Internet	eCommerce	Email
Internet	eCommerce	Events & Ticketing
Internet	eCommerce	Food & Grocery
Internet	eCommerce	Gasoline
Internet	eCommerce	HR & Workforce Management
Internet	eCommerce	Home Furnishings & Improvement
Internet	eCommerce	Jewelry
Internet	eCommerce	Marketplace
Internet	eCommerce	Multi-Product
Internet	eCommerce	Music, Video, Books & Entertainment
Internet	eCommerce	Office Products
Internet	eCommerce	Other Retail
Internet	eCommerce	Pharmacies

Sector	Industry	Subindustry
Internet	eCommerce	Retail & Inventory
Internet	eCommerce	Social
Internet	eCommerce	Sporting Goods
Internet	eCommerce	Toys & Games
Internet	eCommerce	Travel
Internet	eCommerce	Travel (internet)
Internet	eCommerce	eCommerce enablement
Mobile & Telecom	Mobile Commerce	Accounting & Finance
Mobile & Telecom	Mobile Commerce	Apparel & Accessories
Mobile & Telecom	Mobile Commerce	Auction & Classifieds
Mobile & Telecom	Mobile Commerce	Auto
Mobile & Telecom	Mobile Commerce	B2B Commerce
Mobile & Telecom	Mobile Commerce	Comparison Shopping
Mobile & Telecom	Mobile Commerce	Customer Relationship Management
Mobile & Telecom	Mobile Commerce	Digital Goods
Mobile & Telecom	Mobile Commerce	Discount
Mobile & Telecom	Mobile Commerce	Electronics & Appliances
Mobile & Telecom	Mobile Commerce	Food & Grocery
Mobile & Telecom	Mobile Commerce	Gaming
Mobile & Telecom	Mobile Commerce	Gasoline
Mobile & Telecom	Mobile Commerce	HR & Workforce Management
Mobile & Telecom	Mobile Commerce	Home Furnishings & Improvement
Mobile & Telecom	Mobile Commerce	Jewelry
Mobile & Telecom	Mobile Commerce	Marketplace
Mobile & Telecom	Mobile Commerce	Mobile Commerce enablement
Mobile & Telecom	Mobile Commerce	Multi-Product
Mobile & Telecom	Mobile Commerce	Music, Video, Books & Entertainment
Mobile & Telecom	Mobile Commerce	Other Retail
Mobile & Telecom	Mobile Commerce	Payments
Mobile & Telecom	Mobile Commerce	Pharmacies
Mobile & Telecom	Mobile Commerce	Photo
Mobile & Telecom	Mobile Commerce	Supply Chain & Logistics
Mobile & Telecom	Mobile Commerce	Travel (mobile)
Mobile & Telecom	Mobile Soft. & Serv.	Accounting & Finance
Mobile & Telecom	Mobile Soft. & Serv.	Advertising Network or Exchange
Mobile & Telecom	Mobile Soft. & Serv.	Advertising, Sales & Marketing
Mobile & Telecom	Mobile Soft. & Serv.	Application & Data Integration
Mobile & Telecom	Mobile Soft. & Serv.	Application Development
Mobile & Telecom	Mobile Soft. & Serv.	Asset & Financial Management & Trading
Mobile & Telecom	Mobile Soft. & Serv.	Billing, Expense Management and Procurement
Mobile & Telecom	Mobile Soft. & Serv.	Browser Software/Plugins
Mobile & Telecom	Mobile Soft. & Serv.	Business Intelligence, Analytics & Performance Mgmt
Mobile & Telecom	Mobile Soft. & Serv.	Collaboration & Project Management
Mobile & Telecom	Mobile Soft. & Serv.	Compliance
Mobile & Telecom	Mobile Soft. & Serv.	Conferencing & Communication
Mobile & Telecom	Mobile Soft. & Serv.	Content Management
Mobile & Telecom	Mobile Soft. & Serv.	Customer Relationship Management
Mobile & Telecom	Mobile Soft. & Serv.	Data & Document Management
Mobile & Telecom	Mobile Soft. & Serv.	Database Management
Mobile & Telecom	Mobile Soft. & Serv.	Education & Training
Mobile & Telecom	Mobile Soft. & Serv.	Email
Mobile & Telecom	Mobile Soft. & Serv.	Food & Grocery
Mobile & Telecom	Mobile Soft. & Serv.	Gambling
Mobile & Telecom	Mobile Soft. & Serv.	Gaming
Mobile & Telecom	Mobile Soft. & Serv.	Government
Mobile & Telecom	Mobile Soft. & Serv.	Green/Environmental
Mobile & Telecom	Mobile Soft. & Serv.	HR & Workforce Management
Mobile & Telecom	Mobile Soft. & Serv.	Health & Wellness
Mobile & Telecom	Mobile Soft. & Serv.	Healthcare
Mobile & Telecom	Mobile Soft. & Serv.	Information Providers & Portals
Mobile & Telecom	Mobile Soft. & Serv.	Legal
Mobile & Telecom	Mobile Soft. & Serv.	Location-Based & Navigation
Mobile & Telecom	Mobile Soft. & Serv.	Manufacturing, Warehousing & Industrial
Mobile & Telecom	Mobile Soft. & Serv.	Multi-Product
Mobile & Telecom	Mobile Soft. & Serv.	Multimedia & Graphics
Mobile & Telecom	Mobile Soft. & Serv.	Music
Mobile & Telecom	Mobile Soft. & Serv.	Networking & Connectivity
Mobile & Telecom	Mobile Soft. & Serv.	News & Discussion
Mobile & Telecom	Mobile Soft. & Serv.	Operating Systems & Utility
Mobile & Telecom	Mobile Soft. & Serv.	Payments
Mobile & Telecom	Mobile Soft. & Serv.	Personal & Professional Development
Mobile & Telecom	Mobile Soft. & Serv.	Photo
Mobile & Telecom	Mobile Soft. & Serv.	Point of Sale
Mobile & Telecom	Mobile Soft. & Serv.	Real Estate
Mobile & Telecom	Mobile Soft. & Serv.	Scientific, Engineering
Mobile & Telecom	Mobile Soft. & Serv.	Search
Mobile & Telecom	Mobile Soft. & Serv.	Security
Mobile & Telecom	Mobile Soft. & Serv.	Social
Mobile & Telecom	Mobile Soft. & Serv.	Sports
Mobile & Telecom	Mobile Soft. & Serv.	Storage & Systems Management
Mobile & Telecom	Mobile Soft. & Serv.	Supply Chain & Logistics
Mobile & Telecom	Mobile Soft. & Serv.	Testing
Mobile & Telecom	Mobile Soft. & Serv.	Travel
Mobile & Telecom	Mobile Soft. & Serv.	Video
Mobile & Telecom	Mobile Soft. & Serv.	eCommerce enablement

Note: The classification of start-ups per sector, industry, and subindustry was performed by CB Insights, which has implemented this detailed and consistent classification system throughout the years based on the description of the main activities of each start-up included in the dataset. Each start-up was classified in a unique sector-industry-subindustry triad.

APPENDIX II – Chapter III complementary statistics and results

Figure II.1 – Distribution of variables per quarter for worldwide deals

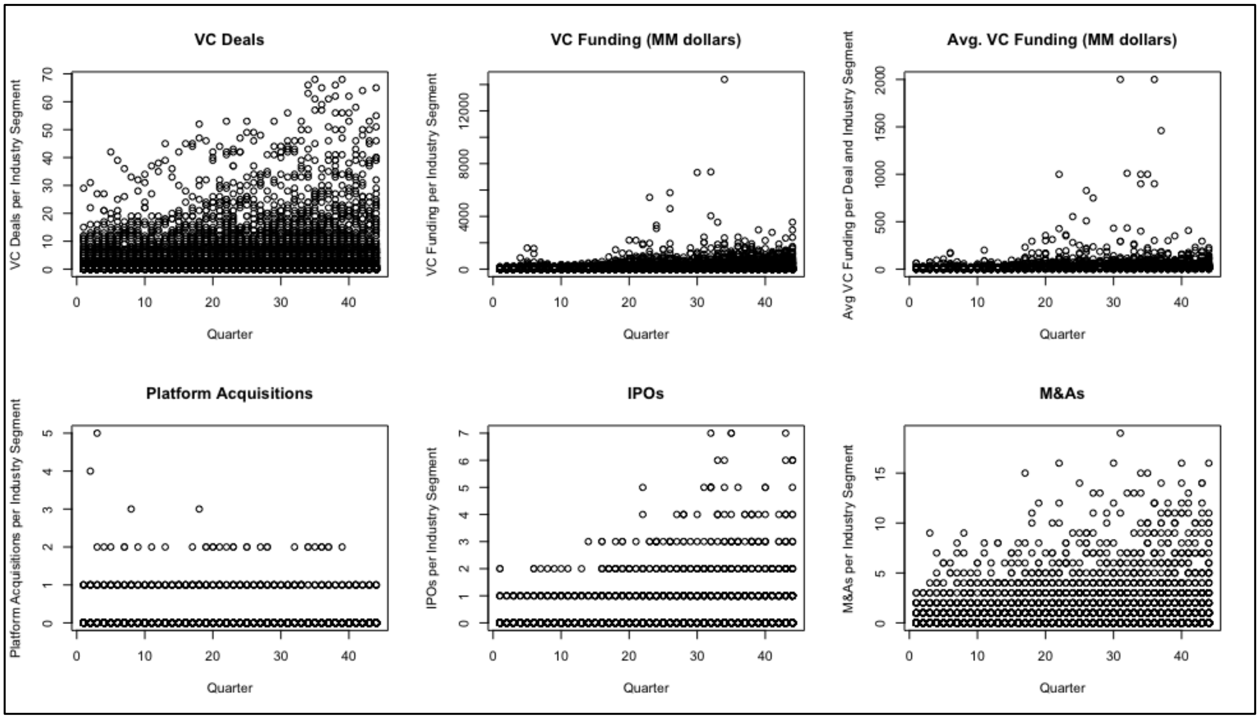


Figure II.2 – Distribution of variables per quarter for U.S. deals

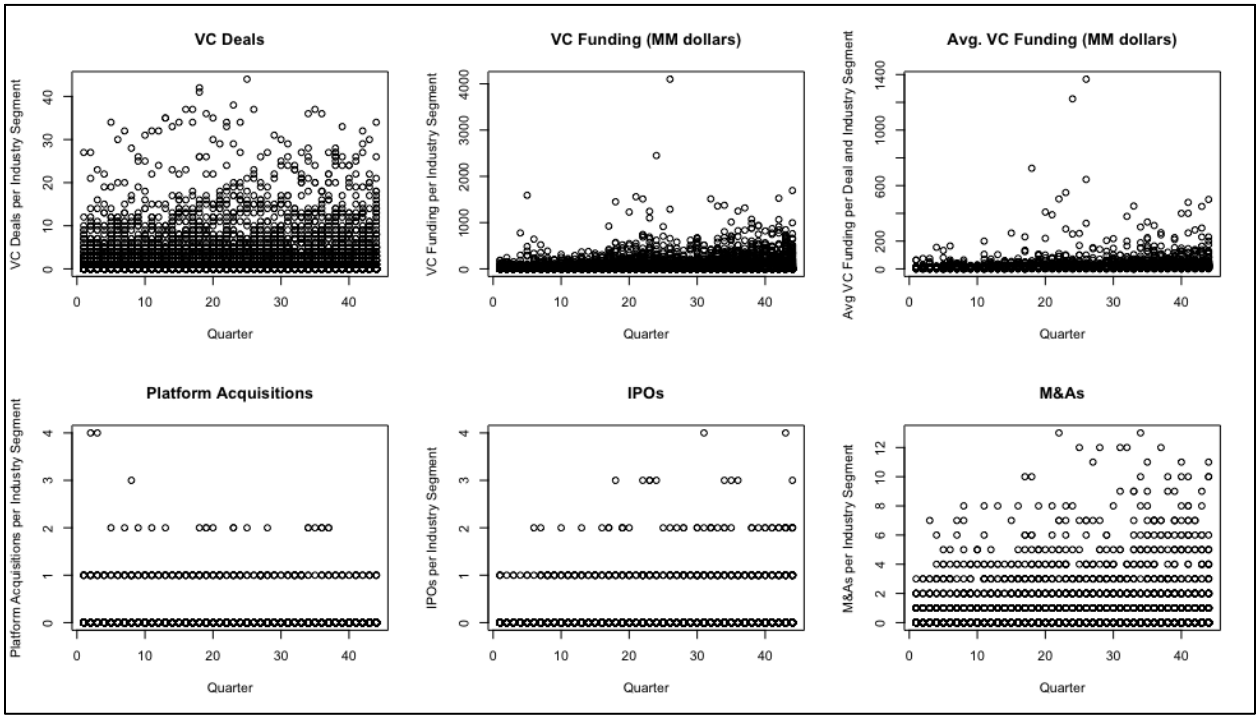


Figure II.3 – Distribution of variables per quarter for European deals

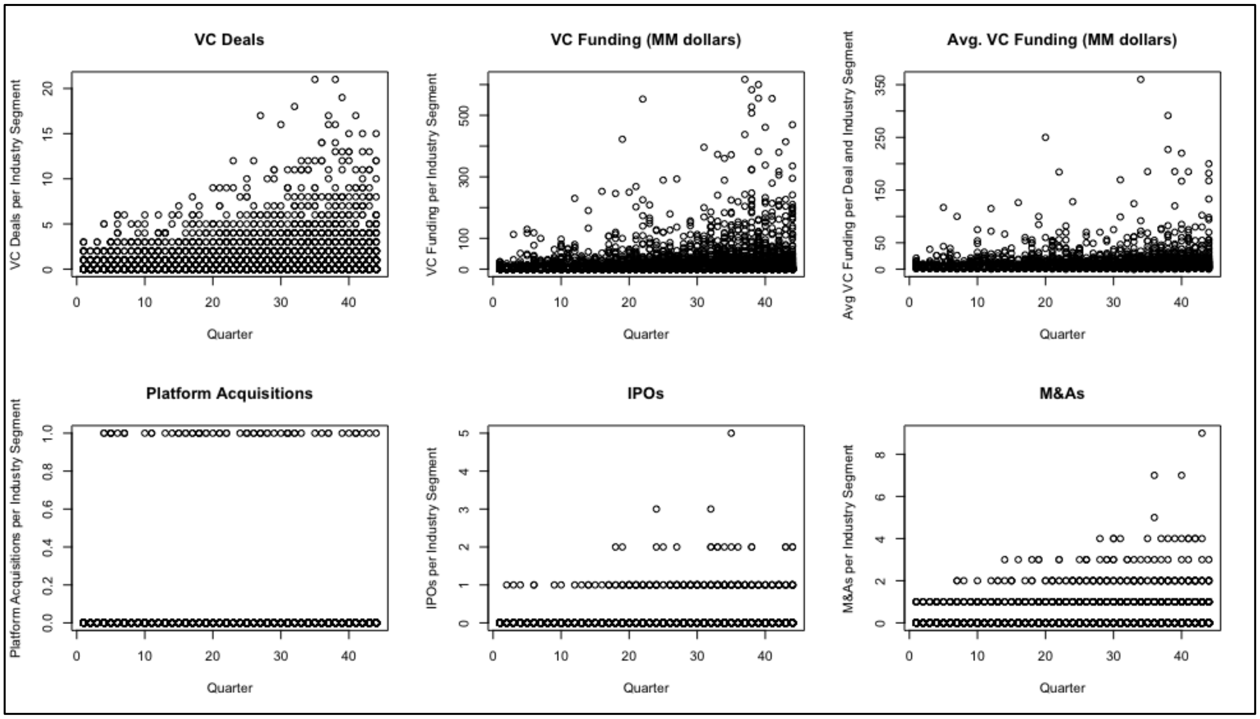
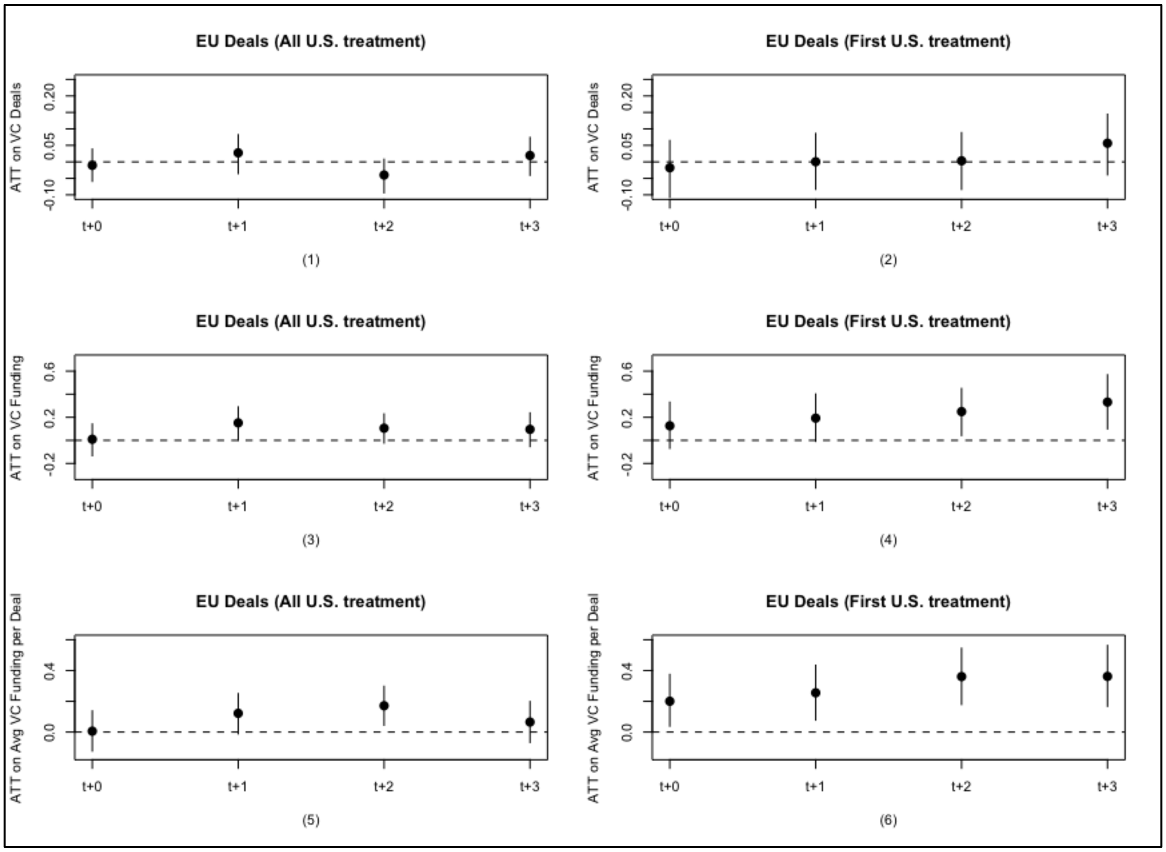


Figure II.4 – Estimated average effects of big tech acquisitions of U.S.-based start-ups on VC activity in Europe



90% confidence intervals based on block-bootstrapped standard errors using 1,000 iterations. For details, see Imai, Kim, and Wang (2021, p.12).
Plots (1), (3), and (5) graphically illustrate the estimated average effects of big tech acquisition of U.S.-based start-ups on the number of VC deals, amount of VC funding, and average VC funding per deal per quarter in Europe, for the quarter of the acquisitions and the three quarters following it, considering all treatment observations.
Plots (2), (4), and (6) graphically illustrate the estimated average effects of big tech acquisition of U.S.-based start-ups on the number of VC deals, amount of VC funding, and average VC funding per deal per quarter in Europe, for the quarter of the acquisitions and the three quarters following it, considering only the very first treatment observations of each industry segment.

Table II.1 – Distribution of VC activity, platform acquisitions, IPOs, and M&As per region

Continent	North Amer.	Europe	Asia	South Amer.	Africa	Oceania	All
Variables							
VC deals	17934	5342	8185	407	139	360	32367
VC funding	345.4	72.4	316.2	9.6	1.8	3.9	749.3
Avg. VC funding	19.3	13.6	38.6	23.7	12.7	10.7	23.2
Plat. Acqui.	312	66	13	0	0	1	392
IPOs	496	260	618	10	4	59	1447
M&As	4147	1118	778	78	4	24	6149

VC funding is reported in billions of U.S. dollars.
Avg VC fund. reports the average amount of funding per VC deal, in millions of U.S. dollars.

Table II.2 – Detailed results of the two-way fixed effects Poisson estimation – Worldwide

Outcome Var.:	VC Deals				VC Fund				Avg. VC Fund			
	(1)	(2)	(3)	(3.F)	(4)	(5)	(6)	(6.F)	(7)	(8)	(9)	(9.F)
main												
plat	0.0298	0.0183	0.0229	0.0240	0.0279	0.0187	0.0197	0.0331	0.0403	0.0355	0.00275	0.0134
	(0.0317)	(0.0318)	(0.0279)	(0.0281)	(0.0762)	(0.0759)	(0.0751)	(0.0725)	(0.0843)	(0.0859)	(0.0929)	(0.0917)
L.plat	0.0627	0.0509	0.0474*	0.0459*	0.0734	0.0698	0.0712	0.0801	0.0962	0.0977	0.0457	0.0470
	(0.0411)	(0.0397)	(0.0259)	(0.0251)	(0.0725)	(0.0792)	(0.0781)	(0.0799)	(0.0813)	(0.0843)	(0.0849)	(0.0860)
L2.plat	0.0812**	0.0711**	0.0704***	0.0679***	0.195*	0.198*	0.198*	0.195*	0.103	0.114	0.0803	0.0842
	(0.0346)	(0.0338)	(0.0197)	(0.0200)	(0.113)	(0.110)	(0.110)	(0.106)	(0.0915)	(0.0927)	(0.0963)	(0.0971)
L3.plat	0.0668**	0.0616*	0.0610***	0.0577***	0.148*	0.119	0.117	0.133	0.0604	0.0456	0.0596	0.0613
	(0.0309)	(0.0323)	(0.0207)	(0.0212)	(0.0844)	(0.0839)	(0.0829)	(0.0814)	(0.0607)	(0.0654)	(0.0715)	(0.0754)
F.plat				0.0111				0.125				0.0531
				(0.0268)				(0.0990)				(0.0989)
ipo		0.0240***	-0.00192	-0.00272		0.00610	0.00424	0.000770		0.00336	0.0233	0.0325
		(0.00824)	(0.00864)	(0.00914)		(0.0331)	(0.0346)	(0.0411)		(0.0526)	(0.0519)	(0.0559)
m&a		0.0133**	-0.00555	-0.00504		-0.00398	-0.00445	-0.00552		0.00313	0.000115	0.00239
		(0.00623)	(0.00445)	(0.00441)		(0.0218)	(0.0209)	(0.0201)		(0.0232)	(0.0226)	(0.0239)
L.ipo		0.00504	-0.0223**	-0.0264***		0.0504*	0.0503*	0.0406		0.0267	0.0276	0.0349
		(0.0125)	(0.00993)	(0.00982)		(0.0272)	(0.0276)	(0.0296)		(0.0374)	(0.0387)	(0.0403)
L2.ipo		0.0115	-0.0147**	-0.0136*		0.00879	0.00677	0.00494		-0.0151	0.0120	0.0113
		(0.00850)	(0.00716)	(0.00765)		(0.0163)	(0.0167)	(0.0164)		(0.0313)	(0.0227)	(0.0234)
L3.ipo		0.00330	-0.0201*	-0.0210*		0.00587	0.00518	0.0152		0.0324	-0.000486	0.00883
		(0.0153)	(0.0115)	(0.0119)		(0.0285)	(0.0289)	(0.0289)		(0.0445)	(0.0366)	(0.0368)
F.ipo				0.00118				0.0398*				0.0227
				(0.00873)				(0.0241)				(0.0309)
L.m&a		0.00853	-0.0103**	-0.0101**		-0.00762	-0.00744	-0.00620		-0.0175	-0.00458	-0.00609
		(0.00524)	(0.00442)	(0.00448)		(0.0139)	(0.0136)	(0.0160)		(0.0209)	(0.0200)	(0.0212)
L2.m&a		0.00325	-0.0143***	-0.0158***		0.0148	0.0149	0.0111		-0.00562	-0.00807	-0.00950
		(0.00618)	(0.00419)	(0.00402)		(0.0118)	(0.0120)	(0.0127)		(0.0154)	(0.0162)	(0.0174)
L3.m&a		-0.00128	-0.0166***	-0.0166***		0.0257	0.0251	0.0119		0.0257	0.0257	0.0218
		(0.00613)	(0.00463)	(0.00455)		(0.0182)	(0.0186)	(0.0215)		(0.0219)	(0.0200)	(0.0233)
F.m&a				0.00125				-0.00399				-0.0275
				(0.00320)				(0.0268)				(0.0266)
L.vcdeals			0.0134***	0.0140***								
			(0.00157)	(0.00160)								
L2.vcdeas			0.0107***	0.00985***								
			(0.00175)	(0.00167)								
L3.vcdeas			0.00701***	0.00672***								
			(0.00186)	(0.00188)								
L4.vcdeas			0.00573***	0.00568***								
			(0.00175)	(0.00184)								
L.vcfund							0.0000313	0.0000192				
							(0.0000432)	(0.0000442)				
L.avg_vcfund											-0.00104***	-0.00117***
											(0.000315)	(0.000316)
N	7093	7093	6920	6747	7093	7093	7093	6920	4408	4408	3787	3688

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table II.3 – Detailed results of the two-way fixed effects Poisson estimation – U.S.

Outcome Var.:	VC Deals				VC Fund				Avg. VC Fund			
	(1)	(2)	(3)	(3.F)	(4)	(5)	(6)	(6.F)	(7)	(8)	(9)	(9.F)
main												
plat	0.0205	0.00550	0.0161	0.0158	0.0823	0.0492	0.0317	0.0216	0.183	0.176	0.211	0.213
	(0.0340)	(0.0325)	(0.0263)	(0.0274)	(0.0677)	(0.0634)	(0.0604)	(0.0646)	(0.143)	(0.140)	(0.157)	(0.157)
L.plat	0.0971**	0.0789**	0.0786***	0.0722***	0.0999***	0.0782**	0.110**	0.0793*	-0.0139	-0.0176	-0.0748	-0.0937
	(0.0398)	(0.0360)	(0.0245)	(0.0241)	(0.0346)	(0.0347)	(0.0474)	(0.0481)	(0.0632)	(0.0661)	(0.0965)	(0.100)
L2.plat	0.125***	0.104***	0.0847***	0.0840***	0.306***	0.283***	0.147**	0.140**	0.155	0.165	0.0471	0.0675
	(0.0351)	(0.0345)	(0.0262)	(0.0264)	(0.111)	(0.106)	(0.0608)	(0.0606)	(0.121)	(0.116)	(0.118)	(0.104)
L3.plat	0.0606	0.0506	0.0310	0.0318	0.195*	0.160	0.0179	0.0173	0.00145	-0.0192	-0.0846	-0.0531
	(0.0410)	(0.0398)	(0.0307)	(0.0317)	(0.102)	(0.0984)	(0.0564)	(0.0554)	(0.101)	(0.102)	(0.0777)	(0.0702)
F.plat				0.0106				0.124				0.0840
				(0.0372)				(0.102)				(0.114)
ipo		0.0288	0.00446	0.00468		-0.0364	-0.0306	-0.0350		-0.131*	-0.0579	-0.0278
		(0.0185)	(0.0178)	(0.0195)		(0.0339)	(0.0331)	(0.0275)		(0.0779)	(0.0531)	(0.0573)
m&a		0.00791	-0.0103*	-0.00953*		0.0112	-0.000506	-0.00286		0.000989	-0.0158	-0.0209
		(0.00777)	(0.00575)	(0.00541)		(0.0151)	(0.0142)	(0.0136)		(0.0166)	(0.0197)	(0.0193)
L.ipo		0.00136	-0.0160	-0.0138		0.0163	0.0252	0.00729		-0.119	-0.0381	-0.0539
		(0.0268)	(0.0227)	(0.0245)		(0.0535)	(0.0507)	(0.0525)		(0.0924)	(0.0848)	(0.0966)
L2.ipo		-0.0183	-0.0181	-0.0151		-0.0340	-0.0139	0.00184		-0.124	-0.0892	-0.0852
		(0.0192)	(0.0154)	(0.0149)		(0.0527)	(0.0493)	(0.0535)		(0.0901)	(0.0669)	(0.0728)
L3.ipo		0.00135	0.0138	0.0105		0.0339	0.0681*	0.0688		-0.132*	-0.0234	-0.0254
		(0.0186)	(0.0182)	(0.0195)		(0.0430)	(0.0400)	(0.0444)		(0.0762)	(0.0595)	(0.0634)
F.ipo				0.0174				-0.00292				-0.175**
				(0.0167)				(0.0334)				(0.0765)
L.m&a		0.0189***	0.00284	0.00490		0.0175	0.00241	0.00310		-0.00447	-0.00739	-0.0103
		(0.00722)	(0.00737)	(0.00736)		(0.0136)	(0.0102)	(0.00994)		(0.0144)	(0.0165)	(0.0166)
L2.m&a		0.0120**	-0.00474	-0.00915		0.0177	0.00927	-0.0105		-0.00544	-0.0319	-0.0354
		(0.00607)	(0.00608)	(0.00567)		(0.0129)	(0.0143)	(0.0153)		(0.0235)	(0.0265)	(0.0276)
L3.m&a		0.000377	-0.0109**	-0.00914*		0.0159	0.0104	0.0148		0.0324	0.0539*	0.0535*
		(0.00689)	(0.00535)	(0.00538)		(0.0173)	(0.0182)	(0.0186)		(0.0286)	(0.0292)	(0.0297)
F.m&a				0.00285				0.0116				0.0122
				(0.00471)				(0.0131)				(0.0223)
L.vcdeals			0.0193***	0.0192***								
			(0.00287)	(0.00282)								
L2.vcdeals			0.0147***	0.0143***								
			(0.00324)	(0.00362)								
L3.vcdeals			0.00904***	0.00823***								
			(0.00303)	(0.00290)								
L4.vcdeals			0.00568**	0.00551**								
			(0.00246)	(0.00238)								
L5.vcdeals			0.00469*	0.00417*								
			(0.00242)	(0.00246)								
L.vcfund							0.000190***	0.000186***				
							(0.0000626)	(0.0000714)				
L2.vcfund							0.000447***	0.000482***				
							(0.000173)	(0.000153)				
L3.vcfund							0.000291***	0.000289***				
							(0.0000904)	(0.0000925)				
L4.vcfund							-0.0000706*	-0.0000806**				
							(0.0000397)	(0.0000397)				
L5.vcfund							-0.0000552	-0.0000814				
							(0.0000822)	(0.0000896)				
L.avg_vcfund											0.00127**	0.00137***
											(0.000516)	(0.000387)
L2.avg_vcfund											0.000719**	0.000671**
											(0.000296)	(0.000285)

L3.avg_vcfund											0.00209***	0.00216***
											(0.000552)	(0.000505)
L4.avg_vcfund											-0.00113*	-0.00126**
											(0.000617)	(0.000608)
L5.avg_vcfund											-0.000273	-0.000370
											(0.000621)	(0.000670)
N	6519	6519	6201	6042	6519	6519	6201	6042	3626	3626	2134	2082

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table II.4 – Detailed results of the two-way fixed effects Poisson estimation – Europe

Outcome Var.:	VC Deals				VC Fund				Avg. VC Fund			
	(1)	(2)	(3)	(3.F)	(4)	(5)	(6)	(6.F)	(7)	(8)	(9)	(9.F)
main												
plat	-0.0951	-0.0986	-0.0993	-0.168	-0.225	-0.264	-0.259	-0.334*	0.106	0.0940	0.0510	0.00536
	(0.120)	(0.120)	(0.123)	(0.139)	(0.168)	(0.169)	(0.167)	(0.183)	(0.272)	(0.263)	(0.319)	(0.337)
L.plat	0.0646	0.0665	0.110	0.0929	0.680*	0.659*	0.667*	0.656*	0.478*	0.475*	0.0198	-0.0415
	(0.119)	(0.119)	(0.110)	(0.123)	(0.359)	(0.374)	(0.370)	(0.372)	(0.248)	(0.258)	(0.219)	(0.213)
L2.plat	0.236*	0.248*	0.310**	0.265*	0.651**	0.666**	0.657**	0.637*	0.563	0.588	-0.0739	-0.115
	(0.143)	(0.149)	(0.153)	(0.137)	(0.302)	(0.312)	(0.316)	(0.329)	(0.398)	(0.400)	(0.340)	(0.354)
L3.plat	-0.104	-0.0964	-0.0720	-0.130	0.221	0.248	0.241	0.222	0.417	0.445	-0.399	-0.446
	(0.140)	(0.147)	(0.143)	(0.135)	(0.377)	(0.382)	(0.382)	(0.401)	(0.467)	(0.465)	(0.450)	(0.516)
F.plat				-0.176				-0.341				-0.421
				(0.177)				(0.223)				(0.391)
ipo		0.0470	0.00403	-0.0230		0.120*	0.117*	0.138**		0.122	0.121	0.170*
		(0.0306)	(0.0285)	(0.0291)		(0.0654)	(0.0667)	(0.0614)		(0.0872)	(0.0861)	(0.0879)
m&a		0.00887	-0.0164	-0.0176		0.0342	0.0312	0.0130		0.00457	0.0422	0.0348
		(0.0177)	(0.0147)	(0.0160)		(0.0392)	(0.0409)	(0.0363)		(0.0532)	(0.0638)	(0.0609)
L.ipo		0.0419	0.0160	-0.0113		0.129	0.125	0.147		0.0368	0.105	0.147
		(0.0260)	(0.0269)	(0.0280)		(0.106)	(0.100)	(0.0924)		(0.0977)	(0.112)	(0.108)
L2.ipo		0.0317	-0.000109	-0.00562		0.0273	0.0170	0.000490		0.0279	-0.0165	-0.00517
		(0.0295)	(0.0254)	(0.0274)		(0.0643)	(0.0656)	(0.0655)		(0.0858)	(0.101)	(0.0949)
L3.ipo		0.000371	-0.0394	-0.0545		0.0827	0.0775	0.0662		-0.00631	0.0949	0.0784
		(0.0432)	(0.0372)	(0.0418)		(0.0628)	(0.0622)	(0.0592)		(0.106)	(0.0736)	(0.0652)
F.ipo				-0.0494				0.0543				0.146*
				(0.0468)				(0.0652)				(0.0836)
L.m&a		-0.00963	-0.0382**	-0.0480***		-0.0361	-0.0410	-0.0133		-0.0230	0.000253	0.0135
		(0.0147)	(0.0167)	(0.0179)		(0.0346)	(0.0356)	(0.0510)		(0.0471)	(0.0529)	(0.0585)
L2.m&a		-0.00104	-0.0398**	-0.0294*		-0.0348	-0.0391	-0.0313		-0.0365	-0.00436	-0.0112
		(0.0167)	(0.0162)	(0.0155)		(0.0383)	(0.0389)	(0.0378)		(0.0459)	(0.0427)	(0.0445)
L3.m&a		-0.000834	-0.0328**	-0.0522***		-0.0261	-0.0312	-0.00572		-0.0268	-0.0464	-0.0253
		(0.0173)	(0.0157)	(0.0178)		(0.0270)	(0.0279)	(0.0348)		(0.0374)	(0.0291)	(0.0442)
F.m&a				0.0346*				-0.0156				-0.0482
				(0.0200)				(0.0316)				(0.0502)
L.vcdeals			0.0155*	0.0162*								
			(0.00825)	(0.00859)								
L2.vcdeas			0.0374***	0.0386***								
			(0.0100)	(0.00928)								
L3.vcdeas			0.0323***	0.0321***								
			(0.00758)	(0.00783)								
L.vcfund.							0.000305	0.000296				
							(0.000393)	(0.000372)				
L2.vcfund							0.000158	0.000188				
							(0.000469)	(0.000502)				
L3.vcfund							0.000186	0.000104				
							(0.000283)	(0.000350)				
L.avg_vcfund											-0.00375**	-0.00510***
											(0.00179)	(0.00196)
L2.avg_vcfund											-0.00232	-0.00261
											(0.00161)	(0.00160)
L3.avg_vcfund											-0.00189	-0.00417***
											(0.00200)	(0.00138)
N	5494	5494	5494	5280	5494	5494	5494	5280	2195	2195	823	787

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

APPENDIX III – Survey Instrument

MSU Study ID: STUDY00006499

Video Streaming Platforms Survey

Start of Block: Phase I - Section 1

Q1.1 Thank you for agreeing to take part in this survey!

This survey is part of an academic study being conducted by the Quello Center at Michigan State University in the United States. This study aims to better understand how internet users respond to digital advertising and the collection of personal data by video streaming service providers. You will receive a more detailed explanation of the study purposes when you have completed your participation.

Please note that your participation in this survey is voluntary, and you can withdraw or refuse to answer any question without penalty. You will be asked questions about your background, your tastes for several types of video content (e.g., sports, cooking, etc.), and your level of engagement with digital platforms. Then you will be asked to watch four short videos (approximately one minute each). After watching the videos, you will be asked questions about your impressions of the videos. The survey will take approximately 20 minutes to complete. Please be assured that the answers you provide will not be linked to you personally. No personally identifiable information (e.g., name, address) will be collected.

If you have any questions or concerns about this research project, please contact the Principal Investigator, Professor Johannes M. Bauer by email at bauerj@msu.edu; by mail at Quello Center, Michigan State University, 404 Wilson Road, Room 406, East Lansing, MI 48824 United States; or by phone at +1 517 432 8005.

To indicate that you have read this consent agreement and that you agree to participate in this online survey, please click the next (>>) button below.

Page Break

Q102 Do you commit to providing thoughtful and honest answers to the questions in this survey?

- I will provide my best answers (1)
- I will not provide my best answers (2)
- I can't promise either way (3)

Skip To: End of Block If Do you commit to providing thoughtful and honest answers to the questions in this survey? != I will provide my best answers

Page Break

Q0 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q0.0 **Before starting Section 1 of this survey, please answer the three screening questions below.**

Q0.1 **What is your current age?**

- ○ Age 18-34 (1)
- ○ Age 35+54 (2)
- ○ Age 55+ (3)

Page Break

Q100 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q0.2 **What is your gender?**

- Male (1)
- Female (2)
- Other (4)
- Prefer not to answer (3)

Page Break

Q101 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q0.3 **In which region of the United States do you currently live?**

- ○ Midwest (1)
- ○ Northeast (2)
- ○ South (3)
- ○ West (4)

Page Break

Q1.2 **Section 1 - In this section we will assess your level of awareness about video streaming platforms**

Page Break

Q1.3 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q1.4 **Below are some of the <u>digital platforms</u> which provide many services through the Internet (e.g., webmail, cloud services, search, social media, video streaming, etc.). Please answer, in your perception, how many users these platforms have <u>in the U.S</u>.**

	Very few users (3)	Few users (4)	Some users (5)	Many users (6)	Very many users (7)
Google (1)	o	o	o	o	o
Yahoo (2)	o	o	o	o	o
Amazon (3)	o	o	o	o	o
Zen Inc. (4)	o	o	o	o	o
Disney (digital services) (5)	o	o	o	o	o
Netflix (6)	o	o	o	o	o
Facebook (7)	o	o	o	o	o
Microsoft (8)	o	o	o	o	o
Apple (9)	o	o	o	o	o

Skip To: End of Block If Below are some of the digital platforms which provide many services through the Internet (e.g., w... = Zen Inc. [Many users]

Skip To: End of Block If Below are some of the digital platforms which provide many services through the Internet (e.g., w... = Zen Inc. [Very many users]

Page Break

Q1.5 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q1.6 **Below are some of the <u>video streaming services</u> available on the Internet. Please answer, in your perception, how many users these video streaming services have <u>in the U.S</u>.**

	Very few users (1)	Few users (3)	Some users (4)	Many users (5)	Very many users (6)
YouTube (1)	○	○	○	○	○
Yahoo Videos (2)	○	○	○	○	○
Hulu (3)	○	○	○	○	○
Disney + (4)	○	○	○	○	○
Vimeo (5)	○	○	○	○	○
Amazon Prime Videos (6)	○	○	○	○	○
HBO Now (7)	○	○	○	○	○
Netflix (8)	○	○	○	○	○
ZenVideos (9)	○	○	○	○	○

Skip To: End of Block If Below are some of the video streaming services available on the Internet. Please answer, in your... = ZenVideos [Many users]

Skip To: End of Block If Below are some of the video streaming services available on the Internet. Please answer, in your... = ZenVideos [Very many users]

Page Break

Q1.7 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q1.8 **Below are some of the <u>video streaming services</u> available on the Internet. Please answer, in your perception, how many users these video streaming services have <u>among your family and friends</u>.**

	Very few users (1)	Few users (3)	Some users (4)	Many users (5)	Very many users (6)
YouTube (1)	○	○	○	○	○
Yahoo Videos (2)	○	○	○	○	○
Hulu (3)	○	○	○	○	○
Disney + (4)	○	○	○	○	○
Vimeo (5)	○	○	○	○	○
Amazon Prime Videos (6)	○	○	○	○	○
HBO Now (7)	○	○	○	○	○
Netflix (8)	○	○	○	○	○
ZenVideos (9)	○	○	○	○	○

Skip To: End of Block If Below are some of the video streaming services available on the Internet. Please answer, in your... = ZenVideos [Many users]

Skip To: End of Block If Below are some of the video streaming services available on the Internet. Please answer, in your... = ZenVideos [Very many users]

Page Break

End of Block: Phase I - Section 1

Start of Block: Phase I - Section 2

Q2.1 **Section 2 - Now, in this section we will assess your level of engagement with video streaming platforms**

Page Break

Q2.2 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q2.3 **Please answer how frequently did you watch videos on the following video streaming platforms in the last month. If you don't use any of them please click never for each one.**

	Never (1)	Rarely (3)	Sometimes (4)	Frequently (5)	Very frequently (6)
YouTube (1)	○	○	○	○	○
Yahoo Videos (2)	○	○	○	○	○
Hulu (3)	○	○	○	○	○
Disney + (4)	○	○	○	○	○
Vimeo (5)	○	○	○	○	○
Amazon Prime Videos (6)	○	○	○	○	○
HBO Now (7)	○	○	○	○	○
Netflix (8)	○	○	○	○	○
ZenVideos (9)	○	○	○	○	○

Skip To: End of Block If Please answer how frequently did you watch videos on the following video streaming platforms in t... = ZenVideos [Frequently]

Skip To: End of Block If Please answer how frequently did you watch videos on the following video streaming platforms in t... = ZenVideos [Very frequently]

Skip To: End of Block If Please answer how frequently did you watch videos on the following video streaming platforms in t... = ZenVideos [Sometimes]

Page Break

Q2.4 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q2.5 **Below are some of the most popular video streaming services in the U.S. Please mark Yes or No for each one that you access through your <u>own</u> subscription or login account. For those platforms that you have never accessed before, mark No.**

	Yes (1)	No (2)
YouTube (1)	○	○
Yahoo Videos (2)	○	○
Hulu (3)	○	○
Disney + (4)	○	○
Vimeo (5)	○	○
Amazon Prime Videos (6)	○	○
HBO Now (7)	○	○
Netflix (8)	○	○
ZenVideos (9)	○	○

Skip To: End of Block If Below are some of the most popular video streaming services in the U.S. Please mark Yes or No for... : = ZenVideos [Yes]

Page Break

Q2.6 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q2.7 **Below are some of the most popular types of videos watched through online video streaming platforms in the U.S (e.g. YouTube). Please answer how frequently did you watch videos of the following types in the last month.**

	Never (1)	Rarely (3)	Sometimes (4)	Frequently (5)	Very frequently (6)
Vlogs (casual, usually unscripted videos of people's everyday lives) (1)	o	o	o	o	o
Comedy skits (short funny videos) (2)	o	o	o	o	o
Videos about animals (3)	o	o	o	o	o
Sports-related videos (4)	o	o	o	o	o

Page Break

Q2.8 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q2.9 **Below are some of the most popular services provided by Google in addition to YouTube. Do you use any of the following? By use we mean access at least once a week.**

	Yes (1)	No (2)
Google Mail (Gmail) (1)	○	○
Google Search (2)	○	○
Google Drive (3)	○	○
Google Maps (4)	○	○
Google News (5)	○	○
Google Chrome (6)	○	○
Google Images (7)	○	○

Page Break

Q2.12 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q2.13 **Please answer how important each the following factors are to your decision about which video streaming platform to use.**

	Not at all important (1)	Low importance (3)	Neutral (4)	Important (5)	Very important (6)
Quality of the content (1)	○	○	○	○	○
Duration of ads (2)	○	○	○	○	○
Privacy concerns (3)	○	○	○	○	○
Price of access (4)	○	○	○	○	○
Previous experience (5)	○	○	○	○	○

Page Break

End of Block: Phase I - Section 2

Start of Block: Phase II - ZenVideos

Page Break

Q3.1 **Section 3 - In this section you will be asked to watch four short videos retrieved from a new streaming service, ZenVideos, and answer some questions.**

Page Break

Q3.2 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q3.3
Please watch this first short video extracted from ZenVideos. Click next when you finish watching.

Tom Brady: Top 10 Plays of the 2019-2020 Season

Page Break

Q3.4 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q3.5 Please read the statements below and mark your level of agreement or disagreement with each one.

When I watch a video like this on a video streaming platform like ZenVideos, ...

	Strongly disagree (1)	Disagree (3)	Neither agree nor disagree (4)	Agree (5)	Strongly agree (6)
I intentionally do not pay attention to the ads. (1)	○	○	○	○	○
I hate the ads. (2)	○	○	○	○	○
It would be better if there were no ads. (3)	○	○	○	○	○
I skip the ads if it is possible. (4)	○	○	○	○	○
The ads make it harder to watch the video. (5)	○	○	○	○	○
Please select "Strongly agree" (11)	○	○	○	○	○
The ads disrupt my viewing of the video. (6)	○	○	○	○	○
The ads distract me from the content of the video. (7)	○	○	○	○	○
The ads interrupt the flow of the video. (8)	○	○	○	○	○
I think the amount of ads on the video is excessive. (9)	○	○	○	○	○

I think the amount of ads on the video is irritating. (10)	○	○	○	○	○
12 (12)	○	○	○	○	○

Skip To: End of Block If Please read the statements below and mark your level of agreement or disagreement with each one. ... != Please select "Strongly agree" [Strongly agree]

Page Break

Q3.6 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q3.7
Please watch this second short video below extracted from ZenVideos. Click next when you finish watching.

Warriors fan crazy show on Dance Cam - Golden State Warriors vs. Dallas Mavericks

---

Page Break

Q3.8 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q3.9 Please read the statements below and mark your level of agreement or disagreement with each one.

When I watch a video like this on a video streaming platform like ZenVideos, ...

	Strongly disagree (1)	Disagree (3)	Neither agree nor disagree (4)	Agree (5)	Strongly agree (6)
I intentionally do not pay attention to the ads. (1)	○	○	○	○	○
I hate the ads. (2)	○	○	○	○	○
It would be better if there were no ads. (3)	○	○	○	○	○
I skip the ads if it is possible. (4)	○	○	○	○	○
The ads make it harder to watch the video. (5)	○	○	○	○	○
The ads disrupt my viewing of the video. (6)	○	○	○	○	○
The ads distract me from the content of the video. (7)	○	○	○	○	○
The ads interrupt the flow of the video. (8)	○	○	○	○	○
I think the amount of ads on the video is excessive. (9)	○	○	○	○	○
I think the amount of ads on the video is irritating. (10)	○	○	○	○	○

Page Break

Q3.10 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q3.11 **Please watch this third short video extracted from ZenVideos. Click next when you finish watching.**

Lebron James best plays ever!

Page Break

Q3.12 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q3.13 Please read the statements below and mark your level of agreement or disagreement with each one.

When I watch a video like this on a video streaming platform like ZenVideos, ...

	Strongly disagree (1)	Disagree (3)	Neither agree nor disagree (4)	Agree (5)	Strongly agree (6)
I intentionally do not pay attention to the ads. (1)	○	○	○	○	○
I hate the ads. (2)	○	○	○	○	○
It would be better if there were no ads. (3)	○	○	○	○	○
I skip the ads if it is possible. (4)	○	○	○	○	○
The ads make it harder to watch the video. (5)	○	○	○	○	○
The ads disrupt my viewing of the video. (6)	○	○	○	○	○
The ads distract me from the content of the video. (7)	○	○	○	○	○
The ads interrupt the flow of the video. (8)	○	○	○	○	○
I think the amount of ads on the video is excessive. (9)	○	○	○	○	○
I think the amount of ads on the video is irritating. (10)	○	○	○	○	○

Page Break

Q3.14 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q3.15 **Please watch this last short video extracted from ZenVideos. Click next when you finish watching.**

FIFA Puskas Award: Best Goal Of The Year

Page Break

Q3.16 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q3.17 Please read the statements below and mark your level of agreement or disagreement with each one.

When I watch a video like this on a video streaming platform like ZenVideos, ...

	Strongly disagree (1)	Disagree (3)	Neither agree nor disagree (4)	Agree (5)	Strongly agree (6)
I intentionally do not pay attention to the ads. (Q3.17_1)	○	○	○	○	○
I hate the ads. (Q3.17_2)	○	○	○	○	○
It would be better if there were no ads. (Q3.17_3)	○	○	○	○	○
I skip the ads if it is possible. (Q3.17_4)	○	○	○	○	○
The ads make it harder to watch the video. (Q3.17_5)	○	○	○	○	○
The ads disrupt my viewing of the video. (Q3.17_6)	○	○	○	○	○
The ads distract me from the content of the video. (Q3.17_7)	○	○	○	○	○
The ads interrupt the flow of the video. (Q3.17_8)	○	○	○	○	○
Please select "Strongly disagree" (Q3.17_11)	○	○	○	○	○

I think the amount of ads on the video is excessive. (Q3.17_9)	○	○	○	○	○
I think the amount of ads on the video is irritating. (Q3.17_10)	○	○	○	○	○

Skip To: End of Block If Please read the statements below and mark your level of agreement or disagreement with each one. ... != Please select "Strongly disagree" [Strongly disagree]

Page Break

Q3.18 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q3.19 **The four videos extracted from ZenVideos were all approximately 1-minute long, including some time spent on ads.**

When you eventually use a video streaming platform like the ZenVideos, what is the maximum length of an ad that you would tolerate before giving up on watching a video <u>that you are really interested in</u>?

	0	5	10	15	20	25	30	35	40	45	50	55	60
Ad maximum length (in seconds) ()													

Page Break

Q3.20

Now, when you eventually use a video streaming platform like the ZenVideos, what is the maximum length of an ad that you would tolerate before giving up on watching a video <u>that you are not really interested in</u>?

	0 5 10 15 20 25 30 35 40 45 50 55 60
Ad maximum length (in seconds) ()	

Page Break

Q3.21 **Section 4 - Now in this section you will be asked to answer some questions about privacy issues related with video streaming platforms.**

Page Break

Q3.22 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q3.23 **Video on-demand services collect information about users' preferences (e.g. topics of interest, location, internet provider, type and brand of device, time that you access, frequency of access, etc.). This information is used to define which ads will be shown to you during the videos as well as while you are using other services of the same platform (e.g. social media, web search, web browsing, etc). In this context, mark your level of agreement or disagreement with the following statements:**

When I choose watching videos on a video streaming platform like ZenVideos,...

	Strongly disagree (1)	Disagree (3)	Neither agree nor disagree (4)	Agree (5)	Strongly agree (6)
I feel uncomfortable when my information is collected without permission. (1)	○	○	○	○	○
I feel concerned about misuse of my personal information. (2)	○	○	○	○	○
I believe that my personal information will not be safely stored. (3)	○	○	○	○	○
I believe that my personal information will be afterwards shared without permission. (4)	○	○	○	○	○
Privacy concerns play an important role in my choice. (5)	○	○	○	○	○

End of Block: Phase II - ZenVideos

Start of Block: Phase II - YouTube Videos

Page Break

Q4.1 **Section 3 - In this section you will be asked to watch four short videos retrieved from YouTube and answer some questions.**

Page Break

Q4.2 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q4.3
Please watch this first short video extracted from YouTube. Click next when you finish watching.

Tom Brady: Top 10 Plays of the 2019-2020 Season

Page Break

Q4.4 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q4.5 Please read the statements below and mark your level of agreement or disagreement with each one.

When I watch a video like this on a video streaming platform like YouTube, ...

	Strongly disagree (1)	Disagree (2)	Neither agree nor disagree (3)	Agree (4)	Strongly agree (5)
I intentionally do not pay attention to the ads. (1)	○	○	○	○	○
I hate the ads. (2)	○	○	○	○	○
It would be better if there were no ads. (3)	○	○	○	○	○
Please select "Agree" (11)	○	○	○	○	○
I skip the ads if it is possible. (4)	○	○	○	○	○
The ads make it harder to watch the video. (5)	○	○	○	○	○
The ads disrupt my viewing of the video. (6)	○	○	○	○	○
The ads distract me from the content of the video. (7)	○	○	○	○	○
The ads interrupt the flow of the video. (8)	○	○	○	○	○
I think the amount of ads on the video is excessive. (9)	○	○	○	○	○

I think the amount of ads on the video is irritating. (10)	o	o	o	o	o

Skip To: End of Block If Please read the statements below and mark your level of agreement or disagreement with each one. ... != Please select "Agree" [Agree]

Page Break

Q4.6 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q4.7
Please watch this second short video below extracted from YouTube. Click next when you finish watching.

Warriors fan crazy show on Dance Cam - Golden State Warriors vs. Dallas Mavericks

Page Break

Q4.8 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q4.9 Please read the statements below and mark your level of agreement or disagreement with each one.

When I watch a video like this on a video streaming platform like YouTube, ...

	Strongly disagree (1)	Disagree (3)	Neither agree nor disagree (4)	Agree (5)	Strongly agree (6)
I intentionally do not pay attention to the ads. (1)	○	○	○	○	○
I hate the ads. (2)	○	○	○	○	○
It would be better if there were no ads. (3)	○	○	○	○	○
I skip the ads if it is possible. (4)	○	○	○	○	○
The ads make it harder to watch the video. (5)	○	○	○	○	○
The ads disrupt my viewing of the video. (6)	○	○	○	○	○
The ads distract me from the content of the video. (7)	○	○	○	○	○
The ads interrupt the flow of the video. (8)	○	○	○	○	○
I think the amount of ads on the video is excessive. (9)	○	○	○	○	○
I think the amount of ads on the video is irritating. (10)	○	○	○	○	○

Page Break

Q4.10 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q4.11 **Please watch this third short video extracted from YouTube. Click next when you finish watching.**

Lebron James best plays ever!

Page Break

Q4.12 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q4.13 Please read the statements below and mark your level of agreement or disagreement with each one.

When I watch a video like this on a video streaming platform like YouTube, ...

	Strongly disagree (1)	Disagree (3)	Neither agree nor disagree (4)	Agree (5)	Strongly agree (6)
I intentionally do not pay attention to the ads. (1)	○	○	○	○	○
I hate the ads. (2)	○	○	○	○	○
It would be better if there were no ads. (3)	○	○	○	○	○
I skip the ads if it is possible. (4)	○	○	○	○	○
The ads make it harder to watch the video. (5)	○	○	○	○	○
The ads disrupt my viewing of the video. (6)	○	○	○	○	○
The ads distract me from the content of the video. (7)	○	○	○	○	○
The ads interrupt the flow of the video. (8)	○	○	○	○	○
I think the amount of ads on the video is excessive. (9)	○	○	○	○	○
I think the amount of ads on the video is irritating. (10)	○	○	○	○	○

Page Break

Q4.14 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q4.15 **Please watch this last short video extracted from YouTube. Click next when you finish watching.**

FIFA Puskas Award: Best Goal of The Year

Page Break

Q4.16 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q4.17 Please read the statements below and mark your level of agreement or disagreement with each one.

When I watch a video like this on a video streaming platform like YouTube, ...

	Strongly disagree (1)	Disagree (3)	Neither agree nor disagree (4)	Agree (5)	Strongly agree (6)
I intentionally do not pay attention to the ads. (1)	○	○	○	○	○
I hate the ads. (2)	○	○	○	○	○
It would be better if there were no ads. (3)	○	○	○	○	○
I skip the ads if it is possible. (4)	○	○	○	○	○
The ads make it harder to watch the video. (5)	○	○	○	○	○
The ads disrupt my viewing of the video. (6)	○	○	○	○	○
The ads distract me from the content of the video. (7)	○	○	○	○	○
The ads interrupt the flow of the video. (8)	○	○	○	○	○
Please select "Disagree" (11)	○	○	○	○	○
I think the amount of ads on the video is excessive. (9)	○	○	○	○	○

I think the amount of ads on the video is irritating. (10)	o	o	o	o	o

Skip To: End of Block If Please read the statements below and mark your level of agreement or disagreement with each one. ... != Please select "Disagree" [Disagree]

Page Break

Q4.18 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q4.19 **The four videos extracted from YouTube were all approximately 1-minute long, including some time spent on ads.**

In your daily use of a video streaming platform like the YouTube, what is the maximum length of an ad that you would tolerate before giving up on watching a video <u>that you are really interested in</u>?

	0 5 10 15 20 25 30 35 40 45 50 55 60
Ad maximum length (in seconds) ()	

Page Break

Q93 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q4.20 **Now, i****n your daily use of a video streaming platform like the YouTube, what is the maximum length of an ad that you would tolerate before giving up on watching a video <u>that you are not really interested in</u>?**

	0 5 10 15 20 25 30 35 40 45 50 55 60
Ad maximum length (in seconds) ()	

Page Break

Q4.21 **Section 4 - Now in this section you will be asked to answer some questions about privacy issues related with video streaming platforms.**

Page Break

Q4.22 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q4.23 **Video on-demand services collect information about user's preferences (e.g. topics of interest, location, internet provider, type and brand of device, time that you access, frequency of access, etc.). This information are used to define which ads will be shown to you during the videos as well as while you are using other services of the same platform (e.g. social media, web search, web browsing, etc). In this context, mark your level of agreement or disagreement with the following statements:**

When I choose watching videos on a video streaming platform like YouTube,...

	Strongly disagree (1)	Disagree (3)	Neither agree nor disagree (4)	Agree (5)	Strongly agree (6)
I feel uncomfortable when my information is collected without permission. (1)	○	○	○	○	○
I feel concerned about misuse of my personal information. (2)	○	○	○	○	○
I believe that my personal information will not be safely stored. (3)	○	○	○	○	○
I believe that my personal information will be afterwards shared without permission. (4)	○	○	○	○	○
Privacy concerns play an important role in my choice. (5)	○	○	○	○	○

End of Block: Phase II - YouTube Videos

Start of Block: Phase III - Background and Conclusion

Q5.1 **Section 5 - In this last section we will ask you to share some more background information**

Page Break

Q5.6 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q5.7 **Information about income is very important to understand your usage of video streaming platforms. Please indicate the answer that includes your entire household income in (previous year) before taxes. If you are not sure, please give us your best guess.**

- Less than $29,999 (1)
- $30,000 to $59,999 (2)
- $60,000 to $99,999 (3)
- $100,000 to $149,999 (4)
- $150,000 or more (12)
- Prefer not to answer (14)

Page Break

Q5.8 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q5.9 **In which country did you grow up?**

▼ United States of America (1) ... Zimbabwe (1357)

Page Break

Q5.10 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Q5.11 **Choose one or more races that you consider yourself to be:**

- ▢ White (1)
- ▢ Black or African American (2)
- ▢ American Indian or Alaska Native (3)
- ▢ Latino (8)
- ▢ Asian (4)
- ▢ Native Hawaiian or Pacific Islander (5)
- ▢ ⊗Other (6) ____
- ▢ ⊗Prefer not to answer (7)

Page Break

APPENDIX IV – Detailed results of Chapter V

Table IV.1 – Detailed results of the Poisson QMLE estimation of Column (1) of Table 5.6

adavoid	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
str_plt	-.0655011	.019306	-3.39	0.001	-.1033403	-.027662
ad_dur	-.0048435	.0014064	-3.44	0.001	-.0075999	-.0020871
ad_pos	.2070461	.0248098	8.35	0.000	.1584199	.2556724
subs_youtube	.116159	.0282533	4.11	0.000	.0607836	.1715344
u_youtube	-.0505706	.0105045	-4.81	0.000	-.071159	-.0299822
pu_f_youtube	.0116169	.0106669	1.09	0.276	-.0092899	.0325237
pu_youtube	.0236212	.0168932	1.40	0.162	-.0094889	.0567313
sports	-.0788173	.0095553	-8.25	0.000	-.0975454	-.0600893
imp_ads	.0535514	.0115054	4.65	0.000	.0310013	.0761015
imp_exp	.0016677	.0118263	0.14	0.888	-.0215113	.0248468
imp_pric	.0664898	.0141676	4.69	0.000	.0387218	.0942577
imp_priv	-.0222188	.0108596	-2.05	0.041	-.0435033	-.0009343
imp_qual	-.0734795	.0160553	-4.58	0.000	-.1049473	-.0420117
income	.0231692	.0093817	2.47	0.014	.0047814	.0415569
age_gr	-.0314532	.0139117	-2.26	0.024	-.0587197	-.0041867
race						
Asian	.109571	.0809186	1.35	0.176	-.0490265	.2681685
Asian,Native Hawaiian or Pacific Islander	.0960317	.1592086	0.60	0.546	-.2160115	.4080749
Black or African American	-.030089	.0779579	-0.39	0.700	-.1828837	.1227057
Black or African American,Latino	-.0579398	.2589279	-0.22	0.823	-.5654292	.4495497
Latino	.1772357	.0747539	2.37	0.018	.0307208	.3237506
Latino,Asian	.1989512	.0983831	2.02	0.043	.0061238	.3917786
Native Hawaiian or Pacific Islander	.3562757	.0913122	3.90	0.000	.1773072	.5352443
Other	.0489011	.1537629	0.32	0.750	-.2524686	.3502708
Prefer not to answer	.1431566	.0879639	1.63	0.104	-.0292494	.3155626
White	.0305923	.0662318	0.46	0.644	-.0992196	.1604041
White,American Indian or Alaska Native	.220239	.0875579	2.52	0.012	.0486286	.3918494
White,Asian	.2618206	.1595607	1.64	0.101	-.0509126	.5745537
White,Black or African American	.131516	.0932413	1.41	0.158	-.0512335	.3142656
White,Black or African American,Latino	-.070353	.1461655	-0.48	0.630	-.3568321	.2161261
White,Latino	.0714063	.0857227	0.83	0.405	-.0966071	.2394196
White,Latino,Asian	.4822007	.0743771	6.48	0.000	.3364242	.6279772
nation						
Costa Rica	.1262486	.1718244	0.73	0.462	-.2105211	.4630183
France	-.2531809	.2294836	-1.10	0.270	-.7029605	.1965986
Hong Kong (S.A.R.)	.4448648	.198426	2.24	0.025	.0559571	.8337726
India	.8022957	.1679194	4.78	0.000	.4731796	1.131412
Japan	-.4601647	.2807529	-1.64	0.101	-1.01043	.0901009
Pakistan	.3084094	.1803354	1.71	0.087	-.0450414	.6618602
Romania	.4177145	.1676398	2.49	0.013	.0891464	.7462825
South Africa	.7809846	.1668423	4.68	0.000	.4539796	1.10799
Sweden	-.26322	.2424458	-1.09	0.278	-.7384051	.211965
Switzerland	.5772171	.1759776	3.28	0.001	.2323073	.9221268
United States of America	.3307438	.1636515	2.02	0.043	.0099929	.6514948
Viet Nam	-1.154727	.3137694	-3.68	0.000	-1.769703	-.53975
gend						
Male	.0771906	.02182	3.54	0.000	.0344242	.1199569
Other	-.1793482	.100364	-1.79	0.074	-.3760579	.0173616
geo						
Northeast	-.0764974	.0301095	-2.54	0.011	-.135511	-.0174838
South	-.1352174	.0258645	-5.23	0.000	-.1859109	-.0845238
West	-.0430671	.0278556	-1.55	0.122	-.097663	.0115289
_cons	1.609217	.1908386	8.43	0.000	1.23518	1.983253