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TESIS DOCTORAL/ DOCTORAL DISSERTATION

TRES ENSAYOS SOBRE PLATAFORMAS BILATERALES / THREE ESSAYS ON TWO-SIDED PLATFORMS

MOHAMMAD MAHDI TAVALAEI

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Doctoral Thesis Advisor: JUAN SANTALO

Abstract

This dissertation, constituting three studies, is an attempt to investigate the competitive strategies in platform-mediated industries. The first two studies focus on pricing and nonpricing (design) strategies that two-sided platforms implement to balance the conflict of interest between two sides´ users of their ecosystem. In particular, in the first study, I show how platforms react to an increase in within-group competition on one side which enhances the utility of users on the other side, through cross-network externalities. Whereas, the same side users are worse off and forced to compete in a more hostile and competitive market. I also show the differential response and consequences for the firms with a two-sided versus conventional one-sided logic, and depict the former firms, benefiting the cross-subsidization between the two sides, can outperform the latter. The second study explores a common design strategy (and pertaining contingencies) by which platforms harm the users on one side by deferring them and increasing their required waiting time before accomplishing their goal. On the other hand, the platform provides the users on the other side with more exposure and a higher potential demand. The last study is an endeavor to look into the market momentum concept in technology/platform adoption literature from a more comprehensive and dynamic perspective. I assert how platform adoption and success in the market not only does depend on the overall network size but also the rate of increase in the size and updating the complementary product is of much relevance. Importantly, I depict the latter has a substantially higher impact on the platform performance than the former.

To my parents, for the gravity of their presence.

To Pouye, for the imperishable love.

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Prefacio

Ya tengan un perfil más tradicional, como es el caso de los directorios de páginas amarillas o los centros comerciales o uno más bien digital y tecnológico, como sucede con las tarjetas de crédito y los videojuegos, existen numerosas industrias que se organizan en torno a plataformas bilaterales. Este tipo de plataformas median entre grupos de agentes diversos, si bien *interconectados*, a través de lo cual crean valor para ellos. Muchas de las grandes empresas que han salido a bolsa en los últimos años incorporan este tipo de modelo bilateral: Alibaba con un valor de 25.000 millones de dólares; Visa, con 19.700 millones de dólares; Facebook, con 16.000 millones; Twitter, con 2.100 millones; LinkedIn, con 1.200 millones; o Google, con 1.670 millones. Y no sólo eso, nuevas compañías como AirBnB o Über amenazan con producir un impacto sísmico en industrias consolidadas como el taxi o los servicios hosteleros recurriendo a un modelo de plataforma. Abundando en las crecientes investigaciones en este sentido, esta tesis pretende arrojar algo de luz sobre las estrategias competitivas de las plataformas bilaterales.

Los dos primeros capítulos de esta tesis abordan tanto las estrategias tarifarias y no tarifarias que aplican las plataformas bilaterales a múltiples grupos de su ecosistema. El contexto empírico de estos capítulos es la industria aeroportuaria, un sector objeto de menor atención pero que reviste gran interés desde la perspectiva del mercado bilateral. En el primer capítulo, que trata la estrategia tarifaria, analizaremos el impacto de los cambios exógenos que compiten en una de las vertientes de una plataforma bilateral sobre la tarificación óptima de ambas vertientes. Tomaremos en consideración el impacto positivo de las externalidades de redes cruzadas así como el impacto negativo que produce la competencia intra-plataforma. La combinación de dos efectos de signo contrario conduce a una compensación estratégica que la plataforma necesita mantener: de un lado, atraer más agentes al ecosistema y beneficiarse del efecto de refuerzo positivo de la red intergrupal, y de otro la amplificación del efecto negativo de una intensa competencia intragrupal.

Por medio del desarrollo de una modelo formal, y utilizando un trasfondo cuasi-experimental y un diseño de regresión discontinua, advertimos que en la industria aeroportuaria estadounidense un aumento de la competencia entre aerolíneas en un aeropuerto incrementa los ingresos por pasajero en los aeropuertos que adoptan un enfoque bilateral. Por el contrario, los ingresos por aterrizaje de pasajero sólo aumentan en el caso de los aeropuertos con una capacidad restringida. De igual modo, mostraremos que, al enfrentarse a este cambio exógeno en la competencia, el rendimiento de los aeropuertos que aplican un enfoque bilateral supera al de aquellos que optan por una lógica unilateral en su estructura tarifaria.

El segundo capítulo se centra en las estrategias no tarifarias. Estudiamos la forma en que, al introducir un diseño poco optimizado, algunas plataformas sacrifican de forma deliberada, aunque limitada, el tamaño de la red, con lo cual obtienen una mayor rentabilidad. Hemos bautizado esta estrategia como incremento del tiempo de espera. La manipulación del tiempo de espera es una estrategia no tarifaria habitual en muchas plataformas bilaterales, como es el caso de los motores de búsqueda, los portales de comercio electrónico, las revistas o los centros comerciales. Definimos el *tiempo de espera* de la plataforma como el tiempo que invierten los usuarios en manejar o utilizar la plataforma. Si bien los usuarios no son amigos del tiempo de espera en una vertiente, las plataformas tienen incentivos para no minimizarlo y obtener así mayores ingresos de ellos en la otra. Nuestro razonamiento es que el tiempo de espera en una vertiente tiende a aumentar una vez que se externaliza la gestión de la otra. Este efecto se verá magnificado cuando la vertiente externalizada constituye la fuente de ingresos más importante. Además, la concentración en la vertiente externalizada (interna) modera el tiempo de espera positivamente (negativamente). Ponemos a prueba estas hipótesis en la industria aeroportuaria estadounidense y descubrimos que, si bien la mera externalización no incrementa el tiempo de espera, si se combina con la preeminencia de los ingresos y la concentración de la vertiente externalizada, se producen los efectos vaticinados.

En el tercer capítulo, nos concentramos en los entornos digitales, concretamente en la industria de los videojuegos, como contexto empírico. Los estudios anteriores razonan que las plataformas que obtienen una masa crítica de usuarios alcanzan un impulso de mercado y atraen a más usuarios aún. A pesar de que se predice que este efecto de refuerzo retroalimentado llevará a la plataforma (o la tecnología) con la mayor base de usuarios a quedarse con todo el mercado y expulsar a las plataformas (o tecnologías) competidoras, advertimos de la presencia de “defenestradores” en diversos contextos. ¿Por qué existen algunas plataformas capaces de mantener su impulso a lo largo del tiempo mientras que otras lo pierden en favor de las defenestradoras? Abordamos esta cuestión de forma conceptual, revisando el concepto de impulso en sus componentes inerciales y dinámicos, y de forma empírica, estimando los efectos de ambos componentes en la adopción de la plataforma. Inspirados en la Física, conceptualizamos el componente inercial del impulso (esto es, la masa) como las *existencias* de complementos de la plataforma, y el componente dinámico (esto es, la velocidad) como el cambio de tales existencias de un periodo a otro, lo que sería el complemento de *novedad*. Al poner a prueba las hipótesis en la industria estadounidense del videojuego advertimos que las existencias y la novedad afectan de forma positiva a la adopción de la plataforma por parte de los usuarios, pero que la novedad produce un impacto relativamente mayor. Aplicando esta consideración dinámica, intentamos predecir el "punto de inflexión del mercado" al nivel de la generación de agregación tecnológica –el punto en que la masa de usuarios del mercado da el salto a la nueva generación tecnológica.

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Preface

An immense number of industries, from traditional brick-and-mortar industries such as Yellow pages and shopping malls to digital and high-tech ones such as credit cards and video games, are built up around two-sided platforms. These platforms mediate between distinct yet *interconnected* groups of agents through which create value for them. Among the largest IPOs in the last few years, many have a two-sided model: Alibaba, with $25 billion; Visa, $19.7 billion; Facebook, $16 billion; Twitter, $2.1 billion; Linkedin, $1.2 billion; Google, $1.67 billion. Moreover, new ventures like Airbnb or Über threaten to disrupt well-established industries like taxi or hospitality services using a platform model. Pursuing the research upsurge in this regard, this dissertation endeavors to shed more light on competitive strategies in two-sided platforms.

The first two chapters of this dissertation explore both pricing and nonpricing strategies two-sided platforms apply to multiple groups of their ecosystem. The empirical context of these chapters is the airport industry—a less explored yet fruitful context to be studied from two-sided market perspective. In the first chapter addressing the pricing strategy, I analyze the impact of exogenous changes in competition within one side of a two-sided platform on the optimal pricing of both sides. I take into account both the positive impact through cross-network externalities and the negative impact through higher within-platform competition. The combination of two effects of opposite sign leads to a strategic trade-off that platform needs to manage: attracting more agents to the ecosystem and benefiting from the reinforcing positive network effect across groups on one hand, and amplifying the negative effect of an intense intragroup competition as the flip side.

Developing a formal model and using a quasi-experiment setting and a regression discontinuity design, in the U.S. airport industry, I find increased airline competition within an airport increases commercial revenues per passenger in airports that adopt a two-sided approach, while landing revenue per passengers goes up only for capacity-constrained airports. I also show that facing this exogenous change in competition, airports that apply a two-sided approach outperform those that pursue a one-sided logic in their pricing structure.

The second chapter focuses on nonpricing strategies. I study how, in implementing an underoptimized design, some platforms deliberately sacrifice network size to some extent, while gaining higher profitability. I call this strategy as waiting time increase. Manipulating waiting time is a common nonprice strategy in many two-sided platforms such as search engines, e-commerce portals, magazines and shopping malls. I define platform *waiting time* as the time users spend dealing with/within the platform. Even if users on one side dislike waiting time, platforms have an incentive not to minimize it to get extra revenues from users on the other side, who benefit from it. I argue that waiting time for one side tends to increase once the management of the other side is outsourced. This effect will be reinforced when the outsourced side is the more prominent source for revenue generation. Also, concentration on the outsourced (in-house) side moderates waiting time positively (negatively). I test the hypotheses in the U.S. airport industry and find that while merely outsourcing does not increase waiting time, combined with revenue prominence and concentration of outsourced side do have the predicted effects.

In the third chapter, I turn my attention to a digital, particularly video game, industry as the empirical context. Previous studies argue a platform that obtain a critical mass of users will gain market momentum, and further attracts users. Despite this predicted self-reinforcing feedback, which will make the platform (or technology) with the larger installed user base win the whole market and lock out competing platforms (or technologies), we observe “dethroners” in several contexts. Why are some platforms able to sustain momentum over time while others lose it in favor of dethroners? I address this question conceptually, by revisiting the concept of momentum into the inertial and dynamic components, and empirically, by estimating the effects of both components on platform adoption. Drawing from Physics, I conceptualize the inertial component of momentum (i.e., mass) as the *stock* of platform complements, and the dynamic component (i.e., velocity) as the period-by-period change in such stock, or the complement *novelty*. Testing the hypotheses in the U.S. video game industry, I find that both stock and novelty positively affect platform adoption by users, but the novelty has a relatively stronger impact. Applying this dynamic consideration, I try to predict the “market tipping point” at the technology generation aggregate level—the point at which the mass of users in the market switches to the next-generation technology.

Chapter One

What Is the Impact of Within-Platform Competition in Two-Sided Markets?

INTRODUCTION

Companies using platforms as a two-sided market add value by facilitating the interaction between distinct *but interdependent* agent (i.e. platform users) types on two (or more) sides of a market (Eisenmann, Parker, and Van Alstyne, 2006). For instance, e-commerce platforms like eBay help buyers to more easily find sellers and vice versa; the Google search engine makes advertisers visible to readers; video game consoles like PlayStation enable a transaction between game developers and game users; Airbnb fosters transactions between people looking for accommodation and owners of houses and apartments. However not every platform´s action that benefits to one side´s agents is necessarily in the interest of the agents on the other side. In fact, among some of the policy dimensions directly under platform control, platform operators in two-sided markets often need to manage the degree of within-platform competition to balance conflicting interests of agents on the two sides. For instance, while video game developers would like to avoid competition with other video game developers, gamers may prefer more competition among developers to generate better products at lower prices. Similarly, eBay buyers want more competition among eBay sellers, while sellers want less. Hence, platforms face a strategic tradeoff about what is the intensity of within-platform competition that they should allow on each side of the market. Our paper investigates the impact of this tradeoff on platform pricing strategies and performance.

The increasing prevalence of two-sided platforms in the corporate landscape has attracted a great deal of attention from both economics and management researchers (e.g., Armstrong, 2006; Boudreau 2010; Boudreau and Hagiu, 2009; Caillaud and Jullien, 2003; Eisenmann, Parker, and Van Alstyne, 2011; Evans, 2003; Hagiu, 2006; Rochet and

Tirole 2003, 2006). According to this literature, the strong interdependence between the different sides of a platform implies what are called network effects or network externalities (Rochet and Tirole, 2003, 2006). The network effect in two-sided platforms is twofold (Roson, 2005, 2011; Eisenmann *et al.*, 2006). First, there are cross-network externalities or indirect network effects, which arise when the utility of agents on one side depends on the number of agents on the other side. Second, there are intragroup or within-platform externalities or direct network effects, in which agents´ utility also depends on the number of agents on the same side. Often, increasing the number of agents on one side directly harms them, while it indirectly enhances the attractiveness of the platform for the other side´s agents. For instance, in shopping malls, an increase in the number of shops gives buyers variety but forces merchants to compete harder. Similarly, crowding the mall with shoppers costs buyers time but enhances retailers' potential sales. Hence, firm strategies designed for one side of the market need to take into account their effect on the other side of the market.

Nevertheless, the majority of studies on two-sided platforms have focused on the positive impact of a larger installed base driven by indirect network effects,[1] while overlooking the significance of negative within-platform externalities, with a few exceptions (Belleflamme and Toulemonde, 2009; Boudreau, 2010, 2012; Hagiu, 2009). In this paper, we investigate the case in which both positive indirect and negative direct network effects are important, so the platform needs to manage a strategic trade-off: fostering competition within one side hurts agents on that side while benefiting agents on

[1] The studies of the direct network effect are overwhelmingly centered on its positive character, and also isolate it from the indirect network effect, for example studies on product compatibility (for a summary see McIntyre and Subramaniam, 2009).

the other side. More precisely, our paper is related to recent studies that have stressed the potential negative impact of increasing within-platform competition. Cennamo and Santalo (2013) report a trade-off between enhancing competition on one side and securing some agents by exclusive contracts. Boudreau (2010, 2012) shows how within-platform competition may lessen the innovation incentive of complementary product producers.

Our paper is also related to the literature that analyzes how managing the platform ecosystem requires balancing both sides of the market, taking their interdependence into account (Evans, 2003; Rysman, 2009; Gawer and Cusumano, 2002; Iansiti and Levien, 2004). For instance, media platforms and magazines have to decide on the amount of exposure given to advertisements, given that viewers look for less intrusion and advertisers for maximum exposure (Hagiu, 2014; Hagiu and Jullien, 2011); or in the software industry, piracy protection by the software platform such as operating systems makes software developers better off at the expense of end-users who prefer free or low-cost pirate software (Rasch and Wenzel, 2013).

Modern airports are good candidates for study from a two-sided platform perspective (Gillen, 2001). Airports serve two distinct sides of agents—airlines, and commercial retailers in the terminals—whose interaction relies on the passengers who fly on the airlines and buy merchandise in the airport retail stores (Czerny, 2005). There are cross-network externalities, since ceteris paribus commercial retailers will value more an airport with more airlines and therefore more passengers. As platforms, airports can subsidize airlines in order to bring more passengers to the terminals and appropriate higher rents from the commercial retail side (Armstrong, 2007; Ivaldi, Sokullu, and Toru, 2011). Additionally, there are negative within-platform externalities, since both airlines and commercial retailers dislike an increase in same-side competition.

Two characteristics make U.S. airports particularly convenient to this study. First, in the year 2000, the U.S. Congress approved the *Wendell H. Ford Aviation Investment and Reform Act for the Twenty-First Century* (hereafter AIR-21). This legislation mandated that airports subject to particular criteria diminish entry barriers for new airlines. We exploit this change in regulation, which exogenously increased competition within one side of the platform for some airports but not others, to build a difference-in-difference econometric model (and a regression discontinuity design) that allows us to estimate the impact of this change on airport strategy and performance. Second, for historical reasons some airports explicitly take into account both sides of the market when deciding the prices for each side, while other airports specifically price each side of the market independently of the other. Thus, we can estimate the impacts of changes in within-platform competition on airports having different pricing strategies—what we call platform and "nonplatform" airports.

We find that in response to the rise of competition among airlines, airports increased the fees charged to commercial retailers, and as a result commercial revenue per passenger increased by 20 percent on average. This increase was significantly more pronounced for those airports that had a two-sided pricing policy. Landing fees went up as a result of AIR-21, but only in those airports that were capacity-constrained.

Our study contributes to the literature in several ways. First, we add to emerging research on both the negative within-platform and positive cross-network externalities of increasing the number of agents on one side of a platform market (Belleflamme and

Toulemonde, 2009; Cennamo and Santalo; 2013, Boudreau; 2012; Hagiu, 2009), by specifying explicitly how both negative and positive externalities interact to determine the optimal platform pricing policy. Also, while previous research considered the change in within-platform competition as a deliberate act undertaken by the platform operator, we analyze a change forced by the external environment, thus ruling out endogeneity concerns and allowing causal inference. To our knowledge, no study has directly tested how competition within one side of a platform affects the platform's strategy for both sides. Some authors (Godes, Ofek, and Sarvary, 2009; Jin and Rysman, 2012; Seamans and Zhu, 2014) have investigated the effect of changes in *across-platform* competition within one side of the market on the other side. For instance, Seamans and Zhu (2014) report that when local newspapers face stronger competition from Craigslist, they tend to increase subscription prices. However, these studies do not address *within-platform* competition.

Furthermore, this is the first empirical study to examine the impacts of market structure on different business models—two-sided platform versus conventional one-sided—in the same industry. We analyze not only the different firms´ responses to enhanced within-platform competition but also the effect on their performance. Our empirical evidence shows that a two-sided platform approach, benefiting from cross-subsidization pricing, allows airports to cope better with the exogenous shock of AIR-21 and raise their profitability, while nonplatform airports could not.

FORMAL MODEL

We investigate the effect of a rise in within-platform competition on one side on the platform's pricing behavior on both sides. Assume as in Armstrong (2006) that two groups of agents participate on two sides of a monopoly platform. An agent's utility on side i is defined as; $u_i \ = \ \alpha_i \, n_j - \ \beta_i \, n_i - \ p_i$, where p_i is the platform´s price per agent on side i, and $n_i > 0$ and $n_j > 0$ are the numbers of agents on each side. $\alpha_i > 0$ represents that agents on one side positively value the number of agents on the other side; $\beta_i > 0$, introduces the negative direct network effect in the model and represents that they negatively value the number of agents on the same side as themselves. The agents compete with other agents within the same side of the platform; hence increasing the same side participation is detrimental for their utility. We can write the utilities of a side-1 agent and a side-2 agent as follows:

$$u_1 \ = \ \alpha_1 \, n_2 - \ \beta_1 \, n_1 - \ p_1 \ ; u_2 \ = \ \alpha_2 \, n_1 - \ \beta_2 \, n_1 - \ p_2 \, . \qquad (1)$$

Suppose the number of agents on each side is determined by $n_1 \ = \ \emptyset_1 \, (u_1)$; $n_2 \ = \ \emptyset_2 \, (u_2)$ where $\emptyset_i' > 0 \ \forall i$. Assume that the platform incurs a per-agent cost of f_1 and f_2 on each side as agents join the platform. The platform´s profit is $\pi = \ n_1 \, (\, p_1 - \ f_1 \,) + n_2 \, (\, p_2 - \ f_2 \,)$. As in Armstrong´s (2006) model, for simplicity, we consider that the platform offers utilities $\{u_1, u_2\}$, rather than prices $\{p_1, p_2\}$. Therefore, applying expression (1) we can determine the implicit price on each side in terms of utility. After some manipulation the platform´s profit function is

$$\pi(u_1, u_2) = \ \emptyset_1(u_1) \, [\alpha_1 \, \emptyset_2(u_2) - \ \ \beta_1 \, \emptyset_1(u_1) - \ u_1 - \ f_1 \,)] + \ \emptyset_2(u_2) \, [\alpha_2 \, \emptyset_1(u_1) - \beta_2 \, \emptyset_2(u_2) - \ u_2 - \ f_2 \,)] \, . \qquad (2)$$

The platform's profit maximization conditions, $\frac{\partial \pi(u_1,u_2)}{\partial u_1} = 0$ and $\frac{\partial \pi(u_1,u_2)}{\partial u_2} = 0$, lead to the following optimal prices:

$$p_1 = f_1 - \alpha_2 n_2 + \beta_1 n_1 + \frac{\emptyset_1(u_1)}{\emptyset'_1(u_1)} \, ; \; p_2 = f_2 - \alpha_1 n_1 + \beta_2 n_2 + \frac{\emptyset_2(u_2)}{\emptyset'_2(u_2)} \; . \qquad (3)$$

The platform price for a given side 1 is higher the higher is the cost of serving that side´s agents (f_1), and the more harm these agents do to others on the same side ($\beta_1 n_1$). As in Armstrong (2006: 672), the price is lower the higher is the benefit that these agents bring to the other side ($\alpha_2 n_2$). It is also adjusted upwards by a factor "related to the elasticity of the group's participation" ($\frac{\emptyset_1(u_1)}{\emptyset'_1(u_1)}$). Similar logic underpins the price structure on side 2. In other words, the platform rewards agents for enhancing the positive indirect network effect (for the other side´s agents) and penalizes them for amplifying the negative direct one (for the agents on the same side).

For simplicity, we assume that $\emptyset_i (u_i)$ is a linear functional form:

$$\emptyset_1(u_1) = u_1 + a_1 \, ; \emptyset_2(u_2) = u_2 + a_2 \; . \qquad (4)$$

In this particular configuration, we take a_1 and a_2 as the representation of external forces that facilitate entry into the market on each side, increasing both the number of participants and the intensity of competition within that side. By incorporating the specific utility functions as defined in expression (4) into the general expression (3), we can find that

$$p_1 = {}^1\!/_2 \, [\, a_1 + f_1 - n_2 \, . (\alpha_2 - \alpha_1)] \, ; \; p_2 = {}^1\!/_2 \, [\, a_2 + f_2 + n_1 \, . (\alpha_2 - \alpha_1)] \; . \; (5)$$

Without loss of generality we assume that $\alpha_1 < \alpha_2$, so that agents on side 2 gain more from side-1 agents´ presence than vice versa; that is, side-1 agents are more vital for nurturing the positive indirect network effect. Expression (5) then implies that the platform maximizes profit by cutting the price for the agents on the latter side and extracting rent from those on the former side. This skewed pricing structure is called in previous literature as a *divide-and-conquer* strategy (e.g., Belleflamme and Peitz, 2010; Rochet and Tirole, 2006; Weyl, 2010): cutting the price for the agents on one side, to motivate them to be “on board” and boost the cross-network externalities, and then extracting rent by setting a higher price for agents on the other (monetized) side, who are willing to pay more for these externalities.

In a nutshell, expression (5) shows the relative strength of $\{\alpha_1, \alpha_2\}$ specifies which side is the proper candidate to be subsidized or monetized. Moreover, the degree of subsidization/monetization depends on the number of agents on the other side and on the strength of the difference between $\{\alpha_1, \alpha_2\}$, which is the value asymmetry between the two sides for breeding the positive cross-network externalities.

Manipulating (1), (2), and (4) above leads to find that platform´s optimal price on each side is

$$p_1 = a_1 \frac{(1+\beta_1)(1+\beta_2) - \alpha_2\,\bar{\alpha}}{2\,[(1+\beta_1)(1+\beta_2) - \bar{\alpha}^2]} - a_2 \frac{(1+\beta_1)(\alpha_2 - \alpha_1)}{4\,[(1+\beta_1)(1+\beta_2) - \bar{\alpha}^2]} + f_1 \frac{(1+\beta_1)(1+\beta_2) - \alpha_1\,\bar{\alpha}}{2\,[(1+\beta_1)(1+\beta_2) - \bar{\alpha}^2]} + f_2 \frac{(1+\beta_1)(\alpha_2 - \alpha_1)}{4\,[(1+\beta_1)(1+\beta_2) - \bar{\alpha}^2]} \qquad (6)$$

and

$$p_2 = a_1 \frac{(1+\beta_2)(\alpha_2 - \alpha_1)}{4\,[(1+\beta_1)(1+\beta_2) - \bar{\alpha}^2]} + a_2 \frac{(1+\beta_1)(1+\beta_2) - \alpha_1\,\bar{\alpha}}{2\,[(1+\beta_1)(1+\beta_2) - \bar{\alpha}^2]} - f_1 \frac{(1+\beta_2)(\alpha_2 - \alpha_1)}{4\,[(1+\beta_1)(1+\beta_2) - \bar{\alpha}^2]} + f_2 \frac{(1+\beta_1)(1+\beta_2) - \alpha_2\,\bar{\alpha}}{2\,[(1+\beta_1)(1+\beta_2) - \bar{\alpha}^2]} \quad , \qquad (7)$$

where $\bar{\alpha} = \frac{\alpha_1 + \alpha_2}{2}$.

Hence:

$$\frac{\partial p_1}{\partial a_1} = \frac{(1+\beta_1)(1+\beta_2) - \alpha_2\,\bar{\alpha}}{2\,[(1+\beta_1)(1+\beta_2) - \bar{\alpha}^2]}\ ;\ \ \frac{\partial p_2}{\partial a_1} = \frac{(1+\beta_2)(\alpha_2 - \alpha_1)}{4\ [(1+\beta_1)(1+\beta_2) - \bar{\alpha}^2]} \qquad (8)$$

According to the boundary conditions of the model and expression (8), it is straightforward to show that $\frac{\partial p_2}{\partial a_1}$ is always positive. However, $\frac{\partial p_1}{\partial a_1}$ is positive only when the direct network parameters $\{\beta_1, \beta_2\}$ are much higher than the indirect ones $\{\alpha_1, \alpha_2\}$.

Intuitively, when within-platform competition increases on one side, the only determinant of optimal pricing to the agents on the other side is the indirect network effect asymmetry between the two sides. However, the price charged to the agents on the same side is not straightforward and depends on the strength of direct network effect as well. Next, we use the intuition coming from these formal results to build our hypotheses in our empirical context.

EMPIRICAL CONTEXT AND THEORY DEVELOPMENT

The airport industry

Modern airports gain revenue from two distinct sides: aeronautical revenue, which is based on airline-related activities such as landing fees, and nonaeronautical revenue from commercial tenants within terminals, parking, and car rentals concessions (Gillen, 2011). Both sides are subject to negative within-platform competition effects; commercial retailers prefer to be the dominant seller in the terminal, and airlines lose by competing intensively with many other airlines for passengers. Airlines care little about the commercial outlets in the terminals; their main concern is the facilities provided and related charges for aeronautical activities. But commercial retailers do care about the volume of passengers that airlines bring as potential buyers. Thus, the cross-network externalities from airlines to commercial retailers resemble the ones in newspapers, magazines, and other advertising-supported media, in which advertisers crave for more readers/viewers, though the opposite craving is not clear (Evans, 2003; Rysman, 2009; Roson, 2005). Like other two-sided platforms (Rochet and Tirole, 2003, 2006), airports can internalize these externalities by pricing differently for the two sides of the market (Czerny, 2005; Ivaldi *et al*., 2011).

Increase of airline competition in U.S. airports

In 2000, the U.S. Congress passed the *Wendell H. Ford Aviation Investment and Reform Act for the Twenty-First Century* (AIR-21) to diminish entry barriers to U.S. airports and foster competition among airlines. This law, implemented in fiscal year 2001, required all “covered” airports in the United States to submit a competition plan with the Federal Aviation Administration (FAA) to give “new entrant” airlines adequate access to airport facilities such as boarding gates, ticket counters, baggage handling and storage facilities, and take-off and landing slots. Covered airports were those that (1) account for more than 0.25 percent of enplanements at U.S. primary airports and (2) are highly dominated by a few airlines (controlling more than 50% of traffic). For these covered airports, the approval of future federal funds is contingent on a satisfactory competition plan and steps taken to reduce entry barriers for all air carriers willing to serve those airports, with the FAA as the judge. Studies showed that this regulation substantially and efficiently reduced the barriers to entry for new carriers in concentrated airports (e.g., Ciliberto and Williams, 2010; Sinder and Williams, 2015).

Governance model and financing sources of U.S. airports

Most of the commercial airports in the United States "are owned by local governments, such as cities and counties", nevertheless, "some state and local governments have established special entities, such as single-purpose airport authorities or multi-jurisdictional regional authorities, to manage their airports" (FAA/OST Task Force Study, 1999: 2). The main revenue sources of U.S. airports are (i) federal grants or Airport Improvement Program (AIP), (ii) Passenger Facility Charges (PFC),[2] (iii) airside income as specified in the use-and-lease agreements with airlines, (iv) nonairside (commercial side) income as specified in concession contracts, and (v) revenue bonds, which are secured exclusively by revenues from (iii) and (iv) or future income from (ii) (Fuhr and Beckers, 2009).

Despite public governance in most U.S. airports, the major ones involve extensive private control over virtually all aspects of airport planning, design, finance, operations, pricing, and access (de Neufville, 1999). Because of increasing competition, airports have sought to operate in a more businesslike manner by expanding and diversifying their sources of revenue, especially nonairside sources such as retail concessions (Graham, 2008). Although federal sources of funding, AIP and PFCs, are available for public airports, they are greatly dependent on capital markets for their development projects. And since U.S. carriers face a very competitive market, airlines push airports toward efficiency and profitability goals (Carney and Mew, 2003). Although not strictly following

[2] PFCs are charged by airlines at the time of ticket purchase and are then transferred directly to the airports.

the worldwide privatization trend, many airports in the United States have in recent years begun to be organized as quasi-privatized airport authorities.

Competition (in particular between hub airports), limits on governmental funds, restrictive regulation and scrutiny of airline fees, extensive engagement of private third parties in airport businesses, and long-term collaborations with airlines that put pressure on the airports for cost reduction and efficiency all make it quite reasonable to assume that U.S. airports pursue profit (Gillen and Lall, 1997). This extra income allows them to finance future infrastructure investments needed to maximize the connectivity of their regional area of influence.

Theory development

As mentioned earlier, two-sided platforms usually subsidize the agents on one side of the platform to extract money from the other side of the platform, in what is called the divide-and-conquer strategy (Belleflamme and Peitz, 2010; Rochet and Tirole, 2006). The higher the number of agents on the incentivized or *subsidized* side, the higher is the surplus on the other side, so that platforms can inflate the price paid by the agents on this *monetized* side. This cross-subsidized or skewed pricing raises and preserves positive feedback between the two sides´ agents.

In the airport industry, the airlines are the critical agents: it is their passengers who make the airport attractive for retailers. Airports that take account of this externality in their pricing strategy should subsidize landing fees to attract more airlines and flights to the airside, and recover this cost from a mark-up in commercial side prices (Armstrong, 2007; Malavolti, 2010).

Increased competition between airlines that serve the same airport lowers airline ticket prices (Sinder and William, 2015) and should, in turn, benefit the airport's commercial concessionaires. First, lower ticket prices may increase the number of passengers, raising either unit sales or retail prices in airport commercial outlets. Second, lower ticket prices may increase passengers' disposable income and thus airport commercial sales. Airports should take advantage of this presumed increase in retailer profitability and further increase the rents demanded from commercial concessions:

Hypothesis 1. Higher within-airport competition between airlines will increase the price for retailers on the commercial side.

What is the optimal airport pricing strategy for the airside? All else equal, airlines are going to dislike operating in airports with a large number of competitors since this presses the airlines to reduce prices and diminishes profitability prospects. As a direct result of these negative within-platform externalities, airlines will be more reluctant to expand their operations in the now more competitive airports. We call this the "rent dissipation effect," and it should translate into lower airport prices charged to airlines, to partially compensate them for this new more hostile environment. However, a more competitive environment may also affect the balance of power between the airport and airlines. An airport that depends on just a few airlines should have a lower bargaining power to set landing fees; when within-airport competition steepens, the balance of power between airlines and airport shifts in favor of the airport, and as a consequence landing fees should go up. We call this the "bargaining power effect."

The impact of enhanced within-platform competition depends on whether the rent dissipation effect is higher or lower than the bargaining power effect. A priori there is no reason to expect that one should always dominate the other, and therefore we do not have a clear hypothesis about the impact of within-airport competition among airlines on the prices charged by the airport to the airlines. Yet there are some situations in which we can make a straightforward prediction. Take the case of capacity-constrained airports, where the number of flights at regular hours can barely increase. The Industrial Organization literature has documented both conceptually and empirically that binding capacity constraints lower the intensity of competition (Bresnahan and Sulow, 1989; Kreps and Scheinkman, 1983). In our context, when within-airport competition goes up for airlines, the damage to the airlines is going to be lower in capacity-constrained airports, because these airport structurally can only serve a limited number of flights and this weakens or puts a limit for the escalation of battle among the airlines. Hence, in capacity-constrained airports competition is less harmful, so the rent dissipation effect will be lower than the bargaining power effect:

Hypothesis 2. When within-airport competition steps up, airports that are capacity-constrained will increase the price they charge to airlines.

The ability to internalize the network externalities between multiple sides of the market is a critical factor in the two-sided platforms. Some U.S. airports calculate airside charges in a way that prevents them from internalizing the externalities between the airside and the commercial side and makes the divide-and-conquer strategy impossible. There are two types of agreements with airlines by which U.S. airports typically calculate aeronautical charges. Under a so-called *residual* approach, airports set landing fees (and other charges to the airlines) while taking into account both aeronautical and nonaeronautical revenues (Doganis, 1992; Graham, 2008). More specifically, nonaeronautical revenue is used to offset the price charged to signatory airlines, while signatory airlines[3] pledge to cover any potential airport deficit or “residual costs” not covered by airport nonaeronautical revenues. Hence, charges to signatory airlines are determined by the amount of nonaeronautical revenue (and revenue from nonsignatory airlines) deducted from the airport´s full operation costs (Ashford and Moore, 1992). Not surprisingly, informal evidence indicates that airports using residual agreements are under constant pressure by signatory airlines to generate as much revenue as possible out of commercial concessionaires (Richardson, Budd, and Pitfield, 2014).

On the other hand, in a *compensatory* approach, no such cross-subsidization exists. Landing fees are based only on airside revenues and costs (Crider *et al*., 2011; Doganis, 1992; Graham, 2008); indeed, the airport separates aeronautical and commercial operations as independent financial entities. This approach divides all revenues and expenses between the two financially independent profit-cost centers (Rivas, 2002).

Airports with a residual approach behave as two-sided platforms, cross-subsidizing airlines from commercial revenue. This divide-and-conquer strategy is by construction absent in airports using a compensatory approach, so a reduction in airside entry barriers should have little, if any, effect on their commercial price. To recapitulate, when competition increases in the airside, airports lower their airside prices, lest the airlines decrease traffic and/or reduce the quality of services to passengers, thus eventually—through the interdependence of demand between the airside and the

[3] Signatory airlines are those that execute a long-term agreement with a particular airport, while non-signatory airlines operate seasonal or limited services, generally with no signatory agreement.

commercial side (Czerny, 2005)—harming the retailers in terminals as well. However, only under residual agreements can airports apply their commercial revenue to offset airside charges. This generates the standard reinforcing loop that characterizes pricing in two-sided markets: more competition between airlines increases passenger volume and expenditure, raising commercial revenues that then allow increasing commercial rents, which are then used to lower charges to signatory airlines, allowing them to compete yet more fiercely. Airports under compensatory agreements with airlines cannot generate this reinforcing loop. Thus,

Hypothesis 3. Higher within-airport competition between airlines will increase the price for retailers on the commercial side more if they can apply cross-subsidization pricing between the airside and the commercial side.

DATA, METHOD, AND RESULTS

Empirical strategy

The impact of AIR-21 has been studied in previous research, mainly on the airline industry. Most notably, Sinder and Williams (2015) found that AIR-21 significantly decreased airline fares on routes linked to the covered airports—mostly, they contend, by increasing the penetration of low-cost carriers into new markets.

In this study, we turn our attention to the airport as the unit of analysis and examine the effect of AIR-21, via heightening the rivalry among airlines, on both sides of the airport's pricing structure. To do so, we first run a difference-in-difference (hereafter DD) model to investigate the effect of AIR-21 on the dependent variables. DD models are widely used for causal inference when a particular intervention affects part of the sample at a certain time but not the other part (Angrist and Pischke, 2008)—in effect creating a natural experiment with treatment and control groups. This method and the nature of AIR-21 help us to lessen many of the identification strategy problems in two-sided platform studies.

We build a simple DD model as follows:

$$Y_{it} = \psi\, Treat_i \times Post_t + \eta_i + \tau\, Year_t + \phi\, X_{it} + \epsilon_{it}\ , \qquad (9)$$

where Y_{it} denotes the dependent variable at time *t* for airport *i*—namely commercial revenue per passenger, landing revenue per passenger, and airport performance (measured by operating income per passenger and operating ROS). $Treat_i$ and $Post_t$ are the indicators of belonging to the treatment group and being after the AIR-21 intervention, respectively. The interaction of these dummy variables indicates whether the legislation affected observation *i* at time *t*; it equals one only if the airport is a covered one and the time is after 2000. X_{it} is a vector of control variables, and $\boldsymbol{\epsilon_{it}}$ is an error term. Particularly, we are interested in the coefficient of $Treat_i \times Post_t$ to see whether or not the AIR-21 intervention causes a different trend in covered airports than in the rest. We run an OLS regression with robust standard errors clustered at the airport level to deal with the possibility that errors may be correlated among observations belonging to the same airport. We incorporate η_i, airport fixed effects, into the model to deal with time-invariant unobservable factors (Angrist and Pischke, 2008; Bertrand, Duflo, and Mullainathan, 2004).

It could be that airports with specific (unobserved) characteristics may be more likely to be highly concentrated and thus covered by AIR-21. Hence, a simple DD model may suffer from a selection problem (Sinder and Williams, 2015). We apply a regression discontinuity design, described later, to deal with this concern.

Data

We collected longitudinal data on 66 major U.S. airports for ten years from 1996 to 2005. We base our sample on these 66 airports for two reasons. First, these airports are all medium and large hubs (accounting for at least 0.25% of total domestic enplanements); smaller airports are not covered by AIR-21 regardless of their concentration, and for many of these small airports financial data from the FAA are not available. Second, as we capture the Air 21 coverage data from Sinder and Williams (2015), we use the same sample they analyzed.

According to Sinder and Williams (2015), 43 of these airports were immediately covered by AIR-21 and are considered as the treatment group in our natural experiment. The remaining 23 airports were not required to implement any mandatory competition plan (at least until 2005) and thus constitute the control group.[4] The aeronautical and nonaeronautical revenues of the airports, as well as hub status, come from the Federal Aviation Administration (FAA) database, which provides all U.S. airports' annual reports. We also use data from the U.S. Department of Transportation (DOT). DOT's T-100 segment database contains data on all domestic and international yearly flights to/from U.S. airports, including origin and destination airports, number of passengers transported, and name of carrier. We use these data to build our variables for passenger traffic, penetration by low-cost carriers, and the number of airports serving the same city market. We obtain flight delay data from DOT´s On-Time Performance database, and ticket price (in U.S. dollars) for each incoming and outgoing flight from DOT's DB1B database. To

[4] To deal with the possibility of spurious outliers, we excluded from our sample four airport-year observations with values further than three standard deviations from the mean: three for the first dependent variable and one for the second.

determine airports' pricing approaches, we use the results of a 1998 survey conducted by the Airports Council International-North America (ACI-NA)[5] that specifies the type of financial agreement between airport and signatory airlines for about 47 airports, along with the expiration dates of the agreements. As most of these leasing agreements are long-term, we observe no variation within our panel data period in the type of agreement between a given airport and its signatory airlines. Finally, the data on airport ownership and income per capita in each metropolitan statistical area come from the FAA and the U.S. Bureau of Economic Analysis (BSA).

Variables

Dependent variables

We measure price for in-terminal retailers and airlines, respectively, by the natural logarithm of commercial revenue per passenger and landing revenue per passenger. Commercial revenue includes in-terminal revenues to the airport from food and beverage sales, bookstores, gift shops, duty-free shops, and other in-terminal commercial activities such as currency exchanges and advertising.[6] Commercial revenue is reported as one of the critical determinants of airport performance on the nonaeronautical side (Fuerst, Gross, and Klose, 2011). Many airports rely on their concessionaires, most notably retailers and caterers, to generate a significant part of their nonaeronautical revenues. Landing revenue, which constitutes a significant portion of revenue generation on the airside (Doganis, 1992), covers the fees charged to airlines for the use of facilities such as runways, landing strips, runway protection zones, and clearways. In our sample

[5] Reported in FAA/OST Task Force Study, 1999.
[6] Nonaeronautical revenue, excluding Land and non-terminal facilities, rental cars and parking revenue.

commercial revenue represents 27 percent of total airport operating revenue, while landing revenue is 48 percent on average. The rest of airports´ operating revenue consists basically of rent for land and nonterminal facilities, rental car lots, and terminal arrival areas such as check-in and ticket counters; parking fees; and charges for aircraft parking or tiedown.

Independent variables

AIR-21 intervention. We build two dummy variables, one to distinguish treatment from control group (*treat* equals one if the airport is covered by AIR-21 and zero otherwise), and one (*post*) to distinguish years before (1999 to 2000) and after (2001 to 2005) AIR-21 enactment. The coefficient of the interaction term (T*reat* × *Post*) determines the significance of AIR-21 intervention in our difference-in-difference specification (Angrist and Pischke, 2008).

Airport's capacity constraint. Since capacity-constrained airports tend to have higher delays (Chatterji and Zhang, 2007), to measure capacity constraints we split our sample by the annual average of delays in departures and arrivals. The first (fourth) quartile of this variable indicates relatively low (high) delays, and hence identifies airports with low (high) capacity constraints. As mentioned in the theory section, residual-pricing airports cross-subsidize between the airside and commercial side, whereas the compensatory-pricing airports do not.

Airport´s pricing approach. The type of financing arrangement is known for about 47 airports. To test hypothesis three, we split our sample into two subsamples in which all airports implement either residual or compensatory pricing, and exclude airports that combine residual and compensatory agreements with different airlines (12 airports accounting for 97 observations). We do include these “hybrid-pricing approach” airports in the extension analyses to corroborate our findings.

Control variables

The presence of competitors in the market may modify an airport´s pricing strategies. We control for competition among airports by including the number of airport owners that serve the same city market (*city competition*). Roughly forty percent of the airports in our sample are monopolists in their city markets, whereas around forty percent compete with one or two rivals, and twenty percent with three or four. A salient presence of low-cost carriers (LCC) in an airport may affect both the airside, for instance by lowering aeronautical charges (Barrett, 2004; Humphreys, Ison, and Francis, 2006), and the commercial side, by attracting passengers whose purchase profiles differ from those of legacy carrier travelers (Castillo-Manzano, 2010; Graham, 2008). We compute the *LCC penetration* variable as the percentage of all passengers per airport per year who are traveling with low-cost carriers.[7] To rule out any direct effect of change in ticket price on consumers´ expenditure in the terminals, we include (the natural logarithm of) yearly average of ticket price at each airport as a control variable. Finally, the model contains (the natural logarithm of) *income per capita* for the metropolitan statistical area in which each airport is located and a dummy variable for *hub status* (equal to one if large hub, zero otherwise).[8] We apply the natural logarithm transformation as $log(x_j+1)$ and $log(x_j+2)$ for *airport competition* and *LCC penetration*, respectively (Wooldridge, 2013) to mitigate

[7] According to Sinder and Williams (2015), low-cost carriers are B6, FL, F9, G4, J7, KP, KN, N7, NJ, NK, P9, QQ, SY, SX, TZ, U5, VX, W7, W9, WN, WV, XP, and ZA.
[8] Note that the *city competition* and *hub status* variables are excluded from the control variables in the fixed-effect model, because they do not vary across time for each airport.

the skewed distribution caused by one airport per city market or zero percentage of low-cost carriers.

Descriptive statistics

Tables 1 and 2 present the descriptive statistics and correlations of the variables. Pairwise correlations in Table 1 do not show any evidence of multicollinearity. Also, as we expected, there is a significant and negative correlation between *LCC penetration* and both sides' revenue per passenger. Low-cost carriers demand lower landing fees and other aeronautical charges (Barrett, 2000), and their passengers seem less willing to spend money while waiting in the terminals.

TABLE 1
Correlation matrix [a]

Variable	**N**	**mean**	**1**	**2**	**3**	**4**	**5**	**6**
1. Ln(Commercial revenue per passenger)	642	-0.212						
2. Ln(Landing revenue per passenger)	642	0.254	0.292*					
3. Ln(Income per capita)	646	10.400	0.267*	0.228*				
4. Ln(City competition)	656	1.070	0.192*	0.119*	0.309*			
5. Ln(LCC penetration)	656	0.736	-0.219*	-0.295*	-0.000	0.057		
6. Ln(Ticket price)	656	5.902	0.161*	0.293*	0.136*	0.078*	-0-443*	
6. Delay	656	21.011	0.190*	0.146*	0.063*	0.136*	-0.139*	0.138*

All correlations with asterisk are significant at the .05 level.

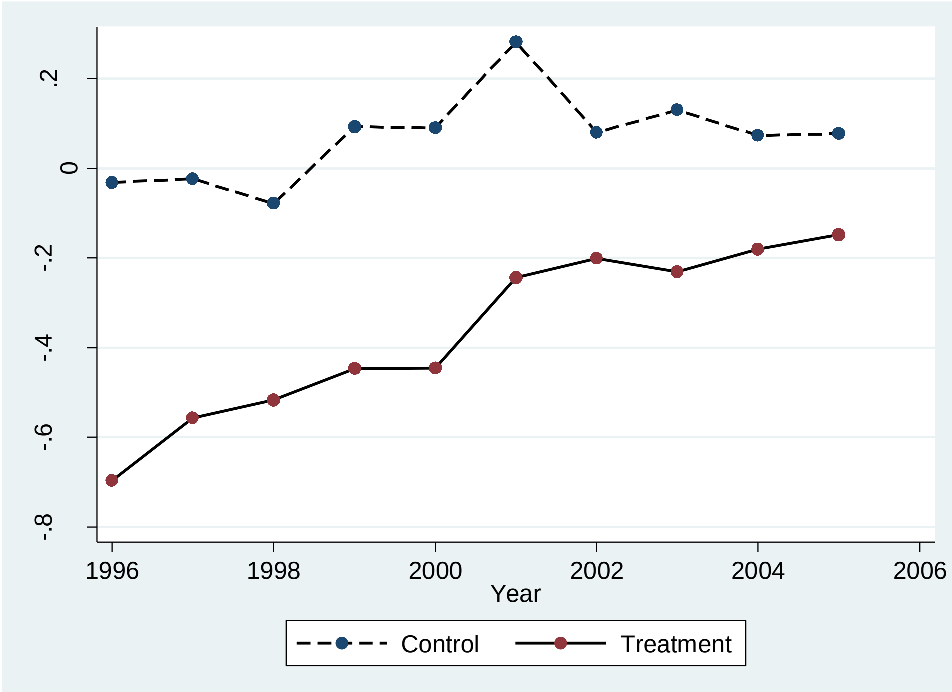
Table 2 shows that overall, treatment and control groups are fairly homogeneous regarding control variables. Hence, we can be reasonably confident that the hypothetical change in dependent variables after AIR-21 is not confounded with substantial heterogeneity in at least these observable parameters. We check this further in the robustness analysis below.

TABLE 2
Descriptive statistics

Variable	**Group**	**N**	**mean**	**min**	**max**
Ln(Commercial revenue per passenger)	***Control***	226	0.070	-2.195	1.921
Ln(Landing revenue per passenger)		225	0.307	-1.145	1.965
Ln(Income per capita)		226	10.379	9.984	10.791
Ln(City competition)		226	1.051	0.693	1.792
Ln(LCC penetration)		226	0.718	0.693	0.888
Ln(Ticket price)		226	5.885	5.340	6.373
Delay		226	21.440	10.685	38.577
Ln(Commercial revenue per passenger)	***Treatment***	416	-0.365	-1.846	1.672
Ln(Landing revenue per passenger)		417	0.226	-1.422	1.884
Ln(Income per capita)		420	10.411	9.928	10.917
Ln(City competition)		430	1.080	0.693	1.792
Ln(LCC penetration)		430	0.745	0.693	1.099
Ln(Ticket price)		430	5.912	3.976	6.318
Delay		430	20.786	11.624	41.128

Figure 1 illustrates briefly the difference trend of covered vs. noncovered airports before and after AIR-21. Panel A, which plots the average of commercial revenue per passenger in every year, shows a modest increasing trend for both noncovered and covered airports before 2000. We expect the trend for noncovered airports to keep rising smoothly, while AIR-21 alters the curve for covered airports. However, the figure demonstrates a dramatic rise in commercial revenue per passenger in year 2001 for both groups. We believe this sharp increase is due to the aftermath of the September 11, 2001 terroristic attack, which caused a dramatic fall in demand for air travel. This sharp decline in the number of passengers, the denominator of our dependent variables, translates into a steep jump in 2001 for these ratios. The drop in passengers in year 2001 is evident in Figure 2 for both groups of airports. As all airports experienced this shock in their passenger demand, this event is not a confounding factor in our analysis. After this shock, the curve for the increase of revenue in noncovered airports continues smoothly and even flattens somewhat, while the growth curve steepens for covered airports—we claim, as a consequence of AIR-21. This pattern is consistent with Figure 1 Panel B for landing revenue per passenger, though the differences in trend after 2000 are not as apparent as in Panel A—an ambiguity that is consistent with our second hypothesis, that the rise of landing charges is contingent on the airport's capacity constraint.

FIGURE 1
Commercial revenue per passenger and Landing revenue per passenger for covered and noncovered airports (treatment and control groups, respectively)
Panel A



Panel B

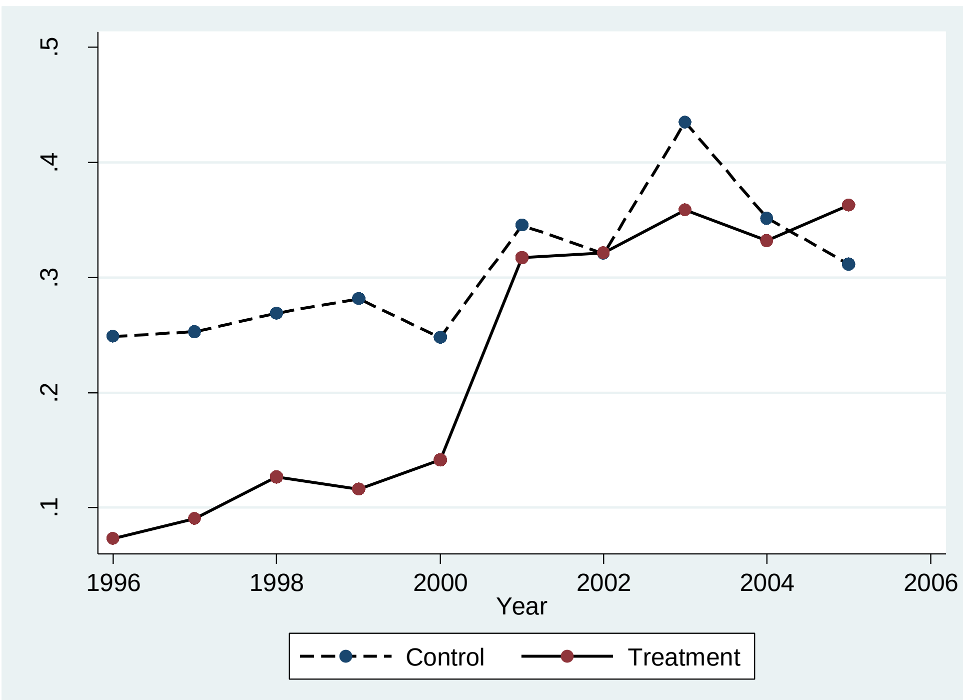


FIGURE 2
Total passenger trend for covered and noncovered airports (treatment and control groups, respectively)

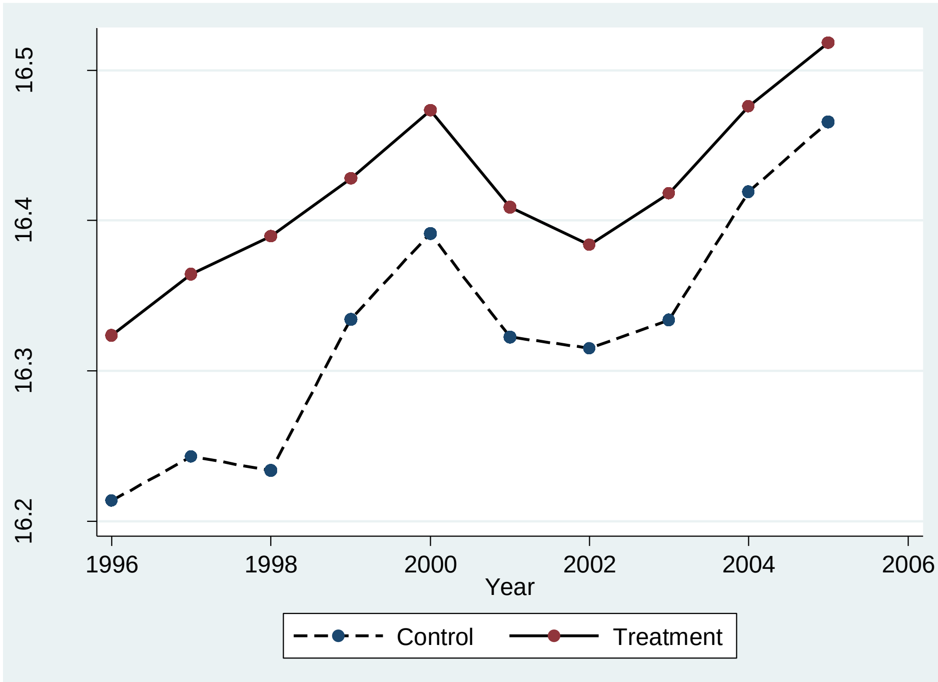


Table 3 translates these graphical patterns into numbers with simple means. First, for each dependent variable, we calculate the averages for the years before and after the enactment of AIR-21. The first difference of each variable is then the difference between averages, computed separately for covered and noncovered airports. The positive numbers imply that both commercial and landing revenue per passenger increased in all airports. Finally, we compute the difference of these first differences between covered and noncovered airports. Table 3 Panel A shows that the natural logarithm of both commercial and landing revenue per passenger grew more after AIR-21 at covered airports than they did at noncovered ones, by 78 and 43 percent respectively. This means that covered airports received 0.26 and 0.22 U.S. dollars more in commercial revenue per passenger and landing revenue per passenger respectively than noncovered airports did after AIR-21. Building the same tables for airports under compensatory and residual agreements separately in Table 3 Panels B and C reveals that, in line with our theoretical reasoning, after AIR-21 commercial revenue per passenger for covered versus noncovered airports increased only for residual-pricing airports and not for those using compensatory pricing. In the next sections, we examine the significance and robustness of this finding in a full-fledged difference-in-difference econometric model.

TABLE 3

Panel A- Difference-in-difference for dependent variables

Variable	**Group**	**Pre AIR-21**		**Post AIR-21**		**1st Diff**	**Diff-in-Diff**
		N	***mean***	***N***	***mean***		
Ln(Commercial revenue per passenger)	***Control***	112	0.009	114	0.128	0.119	0.213
	Treatment	206	-0.532	210	-0.200	0.332	
Ln(Landing revenue per passenger)	***Control***	111	0.259	114	0.353	0.094	0.135
	Treatment	206	0.109	211	0.338	0.229	

Panel B- Difference-in-difference for dependent variables (residual-based airports)

Variable	***Group***	**Pre AIR-21**		**Post AIR-21**		**1st Diff**	**Diff-in-Diff**
		N	***mean***	***N***	***mean***		
Ln(Commercial revenue per passenger)	***Control***	20	0.319	16	0.187	-0.133	1.272
	Treatment	53	-0.503	45	0.636	1.139	
Ln(Landing revenue per passenger)	***Control***	20	0.133	16	-0.095	-0.228	0.555
	Treatment	53	0.056	45	0.384	0.327	

Panel C- Difference-in-difference for dependent variables (compensatory-based airports)

Variable	*Group*	Pre AIR-21 *N*	Pre AIR-21 *mean*	Post AIR-21 *N*	Post AIR-21 *mean*	1st Diff	Diff-in-Diff
Ln(Commercial revenue per passenger)	***Control***	31	0.146	25	0.496	0.350	-0.174
	Treatment	25	-0.151	23	0.025	0.176	
Ln(Landing revenue per passenger)	***Control***	31	0.562	25	0.636	0.075	0.098
	Treatment	25	0.042	23	0.214	0.172	

Results

Table 4 shows the results of the DD model, using as the dependent variable commercial and landing revenue per passenger, as proxies for commercial side and airside prices, respectively. Models 1a and 1b are outcomes of OLS regression with robust standard errors clustered at airport level, after we dropped the extreme observations (see footnote four), whereas models 2a and 2b are results from median regressions keeping all observations. Models 3a and 3b are similar to Models 1a and 1b, while absorbing the airport time-invariant fixed effects.

All models soundly support Hypothesis 1, concerning increased commercial revenue. The coefficient of interaction between *Post* and *Treat* is positive in Models 1a (β= 0.194, $p<0.1$), 2a (β= 0.212, $p<0.01$), and 3a (β= 0.204, $p<0.05$). Specifically, in our sample, in Model 3a we can reject the null hypothesis with a probability of 95.1 percent. The magnitude of the coefficient is also economically significant: AIR-21 coverage leads to a 20 percent (according to the last model) increase in commercial revenue per passenger *ceteris paribus*, a considerable impact. However, AIR21 has no significant effect on landing revenue per passenger (p-value>0.1 in all models).

TABLE 4
Difference-in-difference regression

	Ln(Commercial revenue per passenger)			*Ln(Landing revenue per passenger)*		
Variables	***Model 1a***	***Model 2a***	***Model 3a***	***Model 1b***	***Model 2b***	***Model 3b***
Treat × Post	0.194+	0.212**	0.204*	0.111	0.085	0.129
	(0.104)	(0.065)	(0.102)	(0.088)	(0.123)	(0.083)
Treat	-0.545**	-0.498***		-0.145	-0.046	
	(0.184)	(0.047)		(0.142)	(0.089)	
Post	0.013	0.026		0.053	0.116	
	(0.125)	(0.057)		(0.106)	(0.108)	
Ln(Income per capita)	0.650+	0.808***	-0.831	0.488	0.395+	0.521
	(0.359)	(0.116)	(0.988)	(0.393)	(0.219)	(0.689)
Ln(City competition)	0.181	0.129**		0.190	0.347***	
	(0.198)	(0.046)		(0.175)	(0.087)	
Ln(LCC penetration)	-0.914	-0.525*	-0.404	-1.727*	-1.951***	0.026
	(0.613)	(0.221)	(0.259)	(0.782)	(0.417)	(0.244)
Ln(Ticket price)	0.131	0.086	-0.074	0.557*	0.608***	0.084
	(0.277)	(0.079)	(0.110)	(0.217)	(0.157)	(0.091)
Hub status dummies	YES	YES	NO	YES	YES	NO
Year dummies	NO	NO	YES	NO	NO	YES
Airport fixed effects	YES	YES	YES	YES	YES	YES
Constant	-7.114+	-8.822***	8.748	-6.965	-6.428**	-5.698
	(3.908)	(1.192)	(10.021)	(4.320)	(2.256)	(7.088)
Observations	632	636	632	632	636	632
R^2	0.271		0.252	0.180		0.173
Adjusted R^2	0.262		0.237	0.170		0.156

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Models 1, 2, and 3 are OLS regression with clustered (by airport) robust standard errors, median regression, and clustered robust OLS regression with airport fixed effects, respectively.

We test the second hypothesis by distinguishing between airports with high and low capacity constraints. Table 5 illustrates the results of a DD model with airport fixed effects for the two subsamples.[9] In accord with Hypothesis 2, Air-21 is associated with a roughly 20 percent rise in landing revenue per passenger (β= 0.191, p<0.1) in those airports subject to capacity constraints. For unconstrained airports, we are far from able to reject the null hypothesis. Analysis, not reported here but available upon request,

[9] Comparison of the two subsamples doubles the volume of analysis. Hence, from here on we focus only on the most rigorous model, i.e., the DD model with airport fixed effect.

cannot reject the statistical significance of the difference between these two coefficients; hence, these findings should be considered cautiously.

TABLE 5
Difference-in-difference regression for capacity analysis

	Ln(Landing revenue per passenger)	
Variables	***Low capacity constraints***	***High capacity constraints***
Treat × Post	0.063	0.191+
	(0.129)	(0.109)
Ln(Income per capita)	-0.836	3.224*
	(0.855)	(1.191)
Ln(LCC penetration)	-0.288	0.591
	(0.217)	(0.916)
Ln(Ticket price)	-0.158*	0.151
	(0.068)	(0.122)
Year dummies	YES	YES
Airport fixed effects	YES	YES
Constant	9.577	-34.074**
	(8.924)	(12.201)
Observations	166	150
R^2	0.301	0.428
Adjusted R^2	0.242	0.373

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
All models are OLS regressions with clustered (by airport) robust standard errors.

We test our third hypothesis by splitting the sample into two groups: platform airports (using the residual pricing scheme), and nonplatform airports (using the compensatory scheme). Table 6 shows the results of our main model with airport fixed effects for both subsamples. For airports using compensatory pricing, we do not have any strong evidence against the null hypothesis for the effect of AIR-21 on commercial revenue per passenger (β= -0.221, p>0.1). In contrast, for airports implementing residual pricing, the coefficient of the AIR-21 intervention is positive and significant for commercial revenue per passenger (β= 0.622, p<0.001). In line with Hypothesis 3, AIR-21 leads to higher price increases for commercial retailers in the platform airports, with cross-subsidization pricing structure, than in the nonplatform ones. Indeed, the more than 60 percent increase among platform airports is different from zero with probability above 99 percent. Further analysis, not reported here but available upon request, confirms the statistical significance of the difference between the coefficients of the two subsamples.

TABLE 6
Difference-in-difference regression for airports´ pricing approach

	Ln(Commercial revenue per passenger)	
Variables	***Residual***	***Compensatory***
Treat × Post	0.622***	-0.221
	(0.132)	(0.207)
Ln(Income per capita)	-1.441	-4.400
	(1.617)	(2.525)
Ln(LCC penetration)	-0.315	-0.627
	(0.562)	(0.822)
Ln(Ticket price)	-0.546*	0.500*
	(0.231)	(0.188)
Year dummies	YES	YES
Airport fixed effect	YES	YES
Constant	17.898	42.305
	(15.958)	(25.348)
Observations	134	104
R^2	0.514	0.333
Adjusted R^2	0.461	0.237

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
All models are OLS regressions with clustered (by airport) robust standard errors.

Robustness tests whose results are not reported here but are available upon request corroborate our results. First, we introduce a placebo intervention to the model, faking an arbitrary year as the year of intervention. In no case does the placebo intervention have any effect on the dependent variables. Second, following the advice of Bertrand, Duflo, and Mullainathan (2004), we use a block bootstrap method to deal with potential serial correlation arising from the "intervention variable" itself (in our setting, interaction of the *Post* and *Treat* variables), which may cause over-rejection of the null hypothesis. In this method for creating the bootstrap samples, instead of resampling randomly as in the normal bootstrap process, one keeps together all observations belonging to the same block/cluster (airport in our context; see Bertrand *et al*., 2004; Efron and Tibshirani, 1994).The results we obtain are qualitatively the same.

Regression discontinuity design

One can argue that our dependent variables are likely to correlate with the determinant of AIR-21 coverage, thus our simple DD model suffers from a selection bias. Airports with specific unobservable characteristics may be more likely to be highly concentrated and thus covered by AIR-21 (Sinder and Williams, 2015). To rule out this concern, following Angrist and Pischke (2008), we build a sharp regression discontinuity design as follows:

$$Y_i = \psi D_i + \beta_1 x_i + \beta_1 \tilde{x}_i^2 + \cdots + \beta_p \tilde{x}_i^p + \rho_1 D_i \tilde{x}_i + \rho_2 D_i \tilde{x}_i^2 + \cdots + \rho_p D_i \tilde{x}_i^p + \varepsilon_i \ , \quad (10)$$

To build Y_i as the dependent variable for airport *i,* the natural logarithm of commercial revenue per passenger is averaged for years before (1996-2000) and after (2001-2005) AIR-21 enactment. Subtracting the former average from the latter constructs our dependent variable. According to the first hypothesis, we expect an upward change for the covered compared to the noncovered airports. D_i is a dummy variable indicating whether the given airport *i* is covered by AIR-21 ($Treat_i$).Variable $\tilde{x}_i$ is the concentration of carriers at the airport (x_i) minus the coverage cut-off (x_0=0.50). In other words, it is the airport concentration centered at 0.50 level— $\tilde{x}_i = x_i - x_0$.

The treatment effect at $\tilde{x}$ is $\psi + \rho_1 c + \rho_2 c^2 + \cdots + \rho_p c^p$, where c is the mean of airports concentration centered at coverage cut-off ($x - x_0$), in our sample. Also, ψ and ρ_i are corresponding coefficients resulted from above model. Having these numbers, we compute the magnitude of the treatment effect. Then we apply an F-test to see whether this effect is significantly different from zero. Although additional control variables are not necessarily included in a regression discontinuity design, Imbens and Lemieux (2008) assert that inclusion of these variables can increase the precision of the estimation. We apply models both with and without control variables. The added control variables to expression (10) are constructed identically to the dependent variable describe before. Table 7 indicates the results for linear (where p=1) and quadratic (p=2) models. In accord with Hypothesis 1, we find a positive treatment effect in all models, yet we can reject this effect is significantly different from zero only in quadratic models. In particular, the effect of AIR-21 in Model 2 and 4 is 5.78 and 5.73, and we can reject these numbers are different from zero with the probability of 95.3 and roughly 95 percent, respectively.

TABLE 7
Regression discontinuity analysis

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
	Linear	**Quadratic**	**Linear**	**Quadratic**
Treat	0.050	0.195	0.085	0.154
	(0.787)	(0.416)	(0.635)	(0.506)
$\tilde{x}$	0.693	-11.867	0.751	-11.789
	(0.829)	(0.072)	(0.819)	(0.082)
$\tilde{x}^2$		-92.117		-91.865
		(0.044)	-0.443	(0.051)
Treat × $\tilde{x}$	-0.312	13.225	(0.893)	13.840
	(0.924)	(0.049)		(0.046)
Treat × $\tilde{x}^2$		90.089		88.274
		(0.050)		(0.061)
Control Variables	YES	YES	NO	NO
Constant	0.195	0.104	0.189	-0.028
	(0.587)	(0.789)	(0.220)	(0.877)
Observations	64	64	65	65
R^2	0.108	0.234	0.067	0.207
Adjusted R^2	0.014	0.122	0.021	0.140
Treatment effect	0.012	3.081	0.031	3.125
	$F(1,57)= 0.00$	$F(1,55)=4.06$	$F(1,61)=0.00$	$F(1,59)=3.83$
	p-value=0.981	*p-value=0.048*	*p-value=0.953*	*p-value=0.055*

$\tilde{x}$ is the airport´s concentration centered at coverage cut-off (0.50).
Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Standard errors are robust to heteroskedasticity.

Alternative measure for price in commercial side

One may question our operationalization of price in commercial side by commercial revenue per passenger. The observed increase of this dependent variable could be simply a result of a higher sale in commercial outlets. In this case, if the royalty fees that retailers pay to the airport is determined as a percentage of this sale, airport´s commercial revenue per passenger may increase even with a fixed percentage—without any increase in the royalty fees.

We construct a new sample in which we compile all information about each individual contract between airports and commercial concessions by year. This gives us a dependent variable that is the *real* price charged to commercial concessionaires—the real percentage of commercial sales that the contract allocates to the airport. For this, we directly contacted all 66 airports in our sample to collect the concession contracts between the airports and commercial retailers.[10] For the 14 airports that responded we built a database showing the real percentage of gross sales (for each of five product categories: food and nonalcoholic beverages, liquor, gifts and news, specialty and retail, and duty-free) that concessionaires must pay to the airport. This new dataset contains data about 14 airports, nine of which are covered by AIR-21 and five not covered, for years 1996 to 2005, although we do not have information for all five product categories for all airports in our sample. Table 8 displays the descriptive statistics for this extended dataset. As it shows, with the exception of delay and competition among airports within the city, the means for other control variables are fairly similar for both covered and

[10] Typically the concessionaire pays a fixed rental (Minimum Annual Guarantee [MAG]) or a percentage of gross sales by the concessionaire, whichever is greater.

noncovered groups. Also, within the treatment group we have relatively more observations in the food and nonalcoholic beverage category and fewer in the gifts and news category.

TABLE 8
Descriptive statistics for extended dataset

Variable	**Group**	**N**	**mean**	**min**	**max**
Percentage of in-terminal sales to the airport	***Control***	192	0.123	0.040	0.240
Ln(Income per capita)	***Control***	192	10.374	10.074	10.676
Ln(City competition)	***Control***	192	0.871	0.693	1.099
Ln(LCC penetration)	***Control***	192	0.714	0.693	0.841
Ln(Ticket price)	***Control***	192	5.857	5.440	6.129
Delay	***Control***	192	21.321	16.021	30.058
Percentage of in-terminal sales to the airport	***Treatment***	224	0.138	0.070	0.205
Ln(Income per capita)	***Treatment***	224	10.438	10.130	10.847
Ln(City competition)	***Treatment***	224	1.007	0.693	1.792
Ln(LCC penetration)	***Treatment***	224	0.716	0.693	0.994
Ln(Ticket price)	***Treatment***	224	5.968	5.462	6.318
Delay	***Treatment***	224	19.149	12.131	31.807

Product category	***Percentage of observations in the sample***		
	Control	***Treatment***	***Whole sample***
Food and Nonalcoholic Beverages	32.29	44.20	38.7
Liquor	11.98	12.95	12.5
Gifts and News	39.58	29.02	33.89
Specialty and Retail	11.46	12.05	11.78
Duty-Free	4.69	1.79	3.13

With the real royalties as the dependent variable, we start by implementing in the new sample a DD model similar to the one implemented above, while controlling for both airport and product category fixed effects. Model 1 in Table 9 displays the results, which are qualitatively the same as the ones reported above. Those airports subject to AIR-21 increase the percentage of gross sales that concessionaires pay to the airport by more than one percent ($\beta=0.011$, $p < 0.05$). Given that in our sample the average commercial revenue is $213 million, that one percent increase in royalty on average represents a $213,000 increase in commercial revenue. This lends further support to Hypothesis 1.

TABLE 9
Difference-in-difference regression (extended dataset to airport-product category)

	Model 1	***Model 2***
Variables	***Percentage of in-terminal sales to the airport (whole sample)***	***Percentage of in-terminal sales to the airport (0.2 window)***
Treat × Post	0.011*	0.116*
	(0.012)	(0.016)
Ln(Income per capita)	0.010	0.028
	(0.807)	(0.533)
Ln(Landing revenue per passenger)	-0.043*	-0.051*
	(0.043)	(0.042)
Ln(LCC penetration)	-0.001	-0.023
	(0.960)	(0.430)
Ln(Ticket price)	-0.007	-0.013+
	(0.537)	(0.086)
Year dummies	YES	YES
Airport fixed effect	YES	YES
Product category fixed effect	YES	YES
Constant	0.750	0.708
	(0.177)	(0.243)
Observations	416	164
R^2	0.759	0.834
Adjusted R^2	0.739	0.809

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
All models are OLS regressions with clustered (by airport) robust standard errors.

To deal with the potential selection bias mentioned earlier, however, we cannot apply a regression discontinuity design properly in this new sample. This is an imbalanced panel dataset of 48 airport-product category for 1996 to 2005 (416 observations in total).Our dependent variable for regression discontinuity design, defined as the difference between the average of royalty fees before and after AIR-21, leads to a sample of maximum 48 observations. Nevertheless, for a given airport-product category we do not have enough data for both before and after AIR-21 periods which leads to a dramatically small sample of roughly 29 observations. Because of the inconvenience of implementing regression discontinuity method, instead, we endeavor to use a window analysis to deal with the selection problem. Following Sinder and Williams (2015) we assume that any unobservable characteristic is likely to be evenly distributed among airports just below and just above the AIR-21 concentration cut-off. Hence, we apply the same DD model using a subsample of 416 airport-product category-year observations that fall within a small window around cut-off (50 percent concentration) to estimate the effect of AIR-21. Model 2 in Table 9 displays for airports with 40 percent to 60 percent concentration (that is, within 0.2 of the coverage cut-off). AIR-21 results in roughly an eleven percent increase ($\beta = 0.116$, $p<0.05$) of royalties to covered airports, which supports our first hypothesis.

EXTENSION

Next, we examine the effect of AIR-21 on airport financial performance for residual-pricing and compensatory-pricing airports. We ran our main DD models with airport fixed effects while considering *operating income per passenger*[11] and return on sales associated with

[11] 13 observations pertaining to seven airports (in both control and treatment groups) have negative operating income. Hence, if we do the natural logarithm transformation and treat those observations as missing data, our findings suffer from probable sample selection bias. Therefore, we do not use the natural logarithm transformation for this ratio.

operating revenue (*operating ROS*) as dependent variables.[12] Table 11 shows no significant effect of AIR-21 on airport performance for airports with compensatory pricing. On the other hand, for airports with residual pricing, AIR-21 led to increases in both operating income per passenger (β= 1.185, $p<0.05$) and operating ROS (β= 0.089, $p<0.1$). We interpret these results using the same logic stated above, under which residual pricing allows the airport to subsidize signatory airlines and thus lessen the rent dissipation effect, eventually reinforcing the positive loop between the commercial side and the airside. Accordingly, residual-pricing airports experience an increase of profitability that does not happen for airports using compensatory pricing. Notice that though not statistically significant, the coefficient of AIR-21 coverage is negative in the subsample of compensatory-pricing airports.

We also apply the same DD model to a subsample of airports using *hybrid* pricing (12 airports in our sample). Hybrid-pricing agreements contain elements of both residual and compensatory approaches. Airports using hybrid pricing allocate only part of their nonaeronautical revenue to airline subsidies. But while residual-pricing airports appropriate all commercial revenue exceeding operational cost, airports under hybrid agreements share this excess revenue with the airlines (Graham, 2008; Rivas, 2002). Compared to compensatory-pricing airports, they benefit from the ability to offset airline charges and diminish the rent dissipation effect to some extent, but compared to residual-pricing airports they suffer both from limitation in this cross-subsidization ability and from

[12] It would be more conclusive if we analyzed this by considering ROA or ROE as an additional measure of performance. However, the huge amount of unreported data on airports´ assets for years earlier than 2000 in the FAA records has made it impossible for us to compute these variables.

lower appropriation of excess commercial revenue. Therefore, we expect the effect of within-airport competition on the performance of hybrid-pricing airports to fall in between the effects for airports with compensatory and residual approaches. Table 10 shows that the coefficients of this effect on operating ROS decrease from residual, to hybrid, to compensatory pricing (β =0.089, p<0.1; β=0.047, p>0.1; β=0.008, p>0.1). The same trend is observable for operating income per passenger, our second proxy of airport performance.

TABLE 10
Difference-in-difference regression for performance

	Residual		***Hybrid***		***Compensatory***	
Variables	***Operating income per passenger***	***Operating ROS***	***Operating income per passenger***	***Operating ROS***	***Operating income per passenger***	***Operating ROS***
	Model 1a	***Model 2a***	***Model 1b***	***Model 2b***	***Model 1c***	***Model 2c***
Treat × Post	1.185*	0.089+	0.413	0.047	-0.038	0.008
	(0.531)	(0.044)	(0.537)	(0.060)	(0.605)	(0.032)
Ln(Income per capita)	5.008	0.341	6.328	0.219	-2.493	0.182
	(5.089)	(0.582)	(5.897)	(0.710)	(8.057)	(0.409)
Ln(LCC penetration)	2.063	0.311	-1.099	-0.026	2.979	0.527**
	(2.015)	(0.237)	(1.926)	(0.205)	(2.568)	(0.159)
Ln(Ticket price)	1.065	0.105	2.153+	0.161	1.010	0.053
	(0.884)	(0.086)	(1.038)	(0.128)	(0.829)	(0.061)
Year dummies	YES	YES	YES	YES	YES	YES
Airport fixed effect	YES	YES	YES	YES	YES	YES
Constant	-57.290	-4.067	-75.147	-2.876	20.655	-2.087
	(48.970)	(5.593)	(60.706)	(7.188)	(80.871)	(4.261)
Observations	134	134	97	97	104	104
R^2	0.279	0.129	0.352	0.244	0.169	0.193
Adjusted R^2	0.201	0.034	0.250	0.126	0.049	0.077

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
All models are OLS regressions with clustered (by airport) robust standard errors.

DISCUSSION

This is the first empirical study in the two-sided market literature that shows the effects of changing competition within one side of the market on prices in both sides of the market. In accord with one basic insight of the platform literature, we find that increased airside competition lets airports increase prices in the other side, for the commercial concessionaires. Furthermore, airport performance seems to improve only for airports that apply a two-sided logic in their pricing strategy.

Our findings stress the relevance of the fundamentally distinct logics of two-sided markets. Consider a standard one-sided setting in which companies have suppliers and customers. In that framework an increase of competition between suppliers should imply diminished input prices. One-sided firms will turn these lower input prices into lower prices for the final consumer in a way that is inversely proportional to residual demand elasticity (Tirole, 1988). This means that in one-sided settings an exogenous competition between suppliers should be associated with lower final consumer prices. In a two-sided setting, in which the firm plays an intermediary role between suppliers and consumers and charges royalty fees to both without purchasing and reselling the good, this traditional logic does not apply; indeed, an opposite effect occurs. In this case, since a higher number of suppliers and more intensive competition among them leads to a higher variety and/or a lower price of the good for consumers, the consumers´ utility increases, and the intermediary firm can then levy a *higher* royalty fee on the consumers. Similarly, Galeotti and Moraga-Gonzalez (2009), applying a theoretical model in a retailer-buyer platform setting, predict that increasing the number of retailers, and thus increasing both variety for buyers and competition among retailers, will cause the platform to decrease the retailers´ royalties but increase the buyers´ charges. But if high product differentiation weakens the competition among retailers, the platform will increase the royalties for retailers as well, in line with our findings for our second hypothesis: landing fees increase only in airports where capacity constraints diminish competition on the airside.

The implications of this distinction are both theoretically and practically far-reaching. We show that in the same industry and a similar situation (increased competition within one of the platform sides), airports that apply a two-sided platform logic outperform those that are restricted to a conventional one-sided approach. Generally speaking, this finding emphasizes the relevance of the two-sided approach when externalities exist between different sides of the market. Firms that better internalize the cross-network externalities manage to benefit; neglecting these feedback loops may result in underperforming. Moreover, for researchers and policy makers studying firm responses to environmental drivers, it is crucial to distinguish between one-sided and two-sided logic. Neglecting this nuance may lead to fallacies of applying one-sided logic in a two-sided situation (Wright, 2004). In particular in the airport industry, Gillen (2011) highlights the significance of this distinction for regulators and managers and calls for rethinking aviation policy and strategy from this perspective. Our study is among the first to answer this call. Particularly, we show that residual/dual till pricing enables an airport to fully internalize the externalities between the commercial side and the airside of its market and behave in accordance with two-sided logic, while compensatory/single till pricing does not. These two systems lead to fundamentally different performances for airports facing a change in within-airport competition among airlines. This difference is highly relevant to the analysis of market definition and market power, and to airport regulation (Gillen, 2011; Starkie, 2001).

Limitations and further research

As a limitation of this study, we have to stress that while we control for competition among airports, most airports in our sample act as local monopolies in their city markets, and in many city markets that do have multiple airports they all belong to the same public entity. This means that future research should investigate the validity of our results and hypotheses in settings with significant competition across platforms. Additionally, detailed historical data about vertical financing agreements between airports and airlines can help to elucidate why airports choose a platform versus nonplatform approach, an important issue that our study does not address. Finally, the positive effect of within-platform competition on platform performance may not apply in all empirical contexts. In particular, Boudreau (2010) and Cennamo and Santalo (2013), studying handheld computing systems and the video game industry respectively, have shown that within-platform competition impairs innovation and product quality, a negative effect that does not apply to our airport setting, since innovation is less critical in the airport industry than in technology platforms.

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Chapter Two

Waiting Time in Platform Markets

INTRODUCTION

We are witnessing an explosion of markets organized around platforms that act as an interface between distinct user types. Mobile operating systems like Android connect application developers and cell phone users; search engines like Google connect advertisers with searchers; Facebook connects users with advertisers and third-party developers; and payment systems like credit cards or Paypal are platforms that facilitate the interaction between buyers and sellers.

The economics literature has devoted a lot of attention to pricing strategies in platform industries (e.g., Hagiu, 2005; 2009a; Rochet and Tirole 2003; 2006; Weyl, 2010). It is widely agreed that pricing is a chief strategy to solve the “chicken-and-egg” coordination problem (Caillaud and Jullien, 2003) and boost positive feedback among users. However, recently some studies have questioned the effectiveness of overemphasizing pricing and argued that other strategies such as governance and contracting and design mechanisms are needed to prevent platform market failure (Boudreau and Hagiu, 2009). Yet, other than pricing strategies and the impact of network effects, we know very little about the effectiveness of other strategies that differentiate platform markets from other more conventional industries.

In the management literature, most of the research has focused on investigating the network externalities that characterize platform markets. With few exceptions, studies are mainly centered on the importance of installed user base and how firms can exceed rivals’ network size. However, an effective strategy is more multifaceted than simply augmenting the number of users on different sides of the market (McIntyre and

Subramaniam, 2009). For instance, Suarez (2005) has affirmed the primacy of ties between the users, rather than total network size. Cennamo and Santalo (2013) have studied the detrimental effects of pursuing simultaneously and with equal intensity several "get-big-fast" strategies. Generally, in these markets, managers need to balance carefully the opposite interests of multiple user types all of whom are essential for platform success. In some situations, strategic trade-offs may accentuate parameters for platform success other than mere network size.

In this paper, we study a widespread design strategy that we call *waiting time increase*. We analyze how, in manipulating waiting time—which is detrimental to one group of users but beneficial to another group—platform owners sacrifice network size to some extent, while gaining higher profitability. Hagiu and Jullien (2011) recently investigated under what conditions a platform intermediary makes it harder for buyers to find their preferred seller. Their main insight is that platforms give up higher total consumer traffic for higher revenues per consumer visit. In other words, platforms accept that some buyers will stop using the platform because of the extra time they need to complete their desired transaction, in exchange for more revenue extracted from the sellers, which will get more exposure to the remaining buyers. As Hagiu and Jullien (20119) point out, this extra time harms buyers in proportion to the opportunity cost of their time. In this study, we argue outsourcing management of one side of the platform tilts platform's owner tendency to increase waiting time for another side's users. More specifically, outsourcing can strength the profit motive on the outsourced side. To be attracted to the platform, third-parties need enough revenue potential to undertake management activities on that side.

Additionally, we study how the relative prominence of revenue on each side affects waiting time. Facing the conflict of interest between users who lose time and other users who gain exposure, platforms will be more willing to increase waiting time if the relative revenue generated on the outsourced side is higher. We also study two other moderators that have opposite effects on the increase in waiting time. Specifically, we hypothesize that concentration on the outsourced side may amplify revenue per user and accordingly may positively moderate waiting time increase. In contrast, concentration on the other side boost the negative impact of the traffic loss, and therefore negatively moderates the relationship between outsourcing and waiting time. As an additional reason, bargaining power of users in each side increases with the concentration in that side, therefore we expect more (less) increase of waiting time for the in-house side when the outsourced (in-house) side is dominated by few users.

We test our hypotheses in the U.S. airport industry. Airports can be seen as platform markets that mediate between airlines/passengers and commercial concessions (Armstrong, 2007; Gillen, 2011). This empirical context is useful for our purposes because we can accurately measure users' waiting time. Furthermore, U.S. airports differ in the organizational mechanisms they use to exploit commercial revenues. While some airports manage their commercial space directly, other airports outsource this management to third parties. We estimate the impact of this organizational variation on waiting time.

This paper contributes to the literature on two-sided platforms and network industries in at least four ways. First, while the platform literature is focused mostly on platform pricing strategies, pricing alone does not guarantee a platform success (Boudreau and Hagiu, 2009).Manipulating waiting time is a common nonprice strategy in many platforms such as search engines, e-commerce portals, magazines, shopping malls, and the like. Our paper motivated by Hagiu and Jullien (2011), is the first empirical inquiry into this phenomenon in management research. Second, contributing to platform design and architecture literature, we attest that, platforms can subtly—and profitably—incorporate some noise and slowness in their design. The findings of this study can be considered as a praise of dawdling and slowness, rather than over-optimization and speed-up in design, under certain circumstances. Third, our paper tries to add to the growing body of knowledge in two-sided platforms' governance. In particular, by considering outsourced vs. in-house management of one side, we show how different governance regimes modify the waiting time scheme and related design decision.

THEORY DEVELOPMENT

Pricing and nonpricing strategies in platforms

As previous literature has argued (e.g., Armstrong, 2006; Caillaud and Jullien, 2003; Rochet and Tirole 2003, 2006), intermediary platforms create value by connecting two sets of users and enabling cross-netwrok (or indirect) network externalities to arise. According to the central tenet of two-sided market theory, (at least) one side's participation in the two-sided platform creates value for other-side participants and (at least) one group of users needs the other group to be "on board" (Evans, 2003; Roson, 2005).

The interdependence of demand between different sides makes it possible for the platform operator to apply different strategies to balance the demand of multiple sides depending upon the relative salience of the indirect network externalities resulting from one side for another (Evans, 2003; Rysman, 2009). It is well established that two-sided platforms typically subsidize users on one side of the market (subsidy side) to attract them in volume, so as to gain the chief portion of their revenue from other (money side) users (Belleflamme and Peitz, 2010; Eisenmann, Parker, and Van Alstyne, 2006). This pricing strategy is a common way to deal with the “chicken-and-egg” coordination problem (Caillaud and Jullien, 2003): in order to attract users on either side, the platform needs a large base of users on the other side. However, Boudreau and Hagiu (2009) argue that to maintain long-term performance and survival; platforms should regulate users’ access and interactions in ways beyond price setting.

Nonprice instruments include regulating access to the platform and/or interaction among users, design rules, governance mechanisms, and contracting choices, which surprisingly have received little attention in management studies (Boudreau and Hagiu, 2009). Indeed, platform design is one of the most eminent drivers of network effects and is one of the strategic decisions in two-sided platforms (Hagiu, 2014; Hagiu and Julien, 2011). Nevertheless, the design of the platform and/or of its focal product is apparently assumed to be an exogenous factor, rather than a strategy that can be manipulated for the sake of platforms’ objectives (McIntyre and Subramaniam, 2009).

Among the scarce studies in this realm, Hagiu and Spulber (2013) have looked at first-party content—products that the platform itself provides, such as video games developed by the console maker. These first-party games compete with those of third-party sellers, but they make the platform more attractive and valuable for buyers. Others (Boudreau, 2010; Parker, and Van Alstyne, 2013) have studied the effect of open vs. closed platform design on innovation among complementary products, meaning to what extent the platform restricts users' participation and complementary product development, and/or imposes exclusivity. Baldwin and Woodard (2009) categorize the principal components of platform architecture as peripheral (with high variety), and core (with low variety). Core components are long-lived and set the rules of interaction among different components of the platform. They argue that the combination of variability and stability allows the platform to evolve, and they conclude that owning and controlling the long-lived components is essential for the platform to avoid imitation by rivals and sustain its competitive position in the market.

Waiting time in two-sided platforms

By providing information, technology, or location, two-sided platforms enable multiple groups of users to exchange and minimize their (shared) transaction cost and/or search cost (Evans and Schmalensee, 2007; Hagiu, 2009b). One of the ways in which these platforms create value is by eliminating information asymmetry between two groups to let users find the best "trading partner," or even providing "quality certification" that allows users to find recommended partners (Hagiu, 2009b: 5). For instance, online retailers such as Amazon allow buyers to customize their preferences and find their desired product more efficiently; eBay lets bidders rank the trustworthiness of sellers, making the trade less risky for future bidders; matchmaker websites apply mathematical algorithms to increase the chance of finding an ideal partner; and shopping malls equip an integrated location to meet different needs of customers at once. Hence, it would seem that platform operators should design the platform to optimize search and intensify the probability of an ideal match (Evans and Schmalensee, 2007).

Nevertheless, there are various counter-evidences that platform owners resist overoptimizing search processes; instead, they leave room for “random encounters” that may eventuate in unplanned exchanges. This scheme can be seen in Roppongi Hills, a big real-estate complex in Tokyo, which invites visitors/residents to get lost in a sophisticated maze of stores and restaurants that subtly forces visitors to explore new shops (Boudreau and Hagiu, 2009; Hagiu 2009b). Hagiu and Jullien (2011) attest that some intermediaries intentionally “divert” searchers from the best choice to a less preferred one. For instance, supermarkets lengthen the distance to the most popular products to make customers walk past others. Some magazine layouts defer readers’ access to editorial content by fronting various advertisement pages. Search engines may mix objective results with some advertising results, reducing the richness of the results and requiring users to navigate more before finding their desired link.

Clearly, buyers are better off with a more optimized search; conversely, at least some sellers are more satisfied if there are some search diversions that make them visible to a broader range of buyers. Hagiu and Jullien (2011, 2013) argue that under certain conditions (depending on sellers’ revenue structure and buyers’ search cost distribution) platforms elect to postpone some buyers’ access to their sought-after sellers. Though the total traffic is reduced by users who cannot tolerate the cost of the “noisy” platform, other users who are less sensitive still use the platform, and for these remaining ones, the search diversion strategy brings a higher average of revenue per user.

More generally, balancing between two sides of the market is fundamental for two-sided platforms. Platform owners must create value for both sides and extract value for themselves (Boudreaue and Hagiu, 2009). Owners usually face a conflict of interest between users' groups, and may use platform design to balance their demands and value quest, has to pursue several strategic trade-offs. One of the widespread and well-established trade-offs can be seen in subsidy versus monetary side, as discussed in the outset. However, there are several instances of other trade-offs beyond the price setting decisions.

Specifically to design strategies, platforms can contain several functions and features in their design, which have to be implemented after evaluating their value and expense to the platform's ecosystem. These design strategic decisions may encompass conflicts of interest between the different sides' users (Hagiu, 2014). Rasch and Wenzel (2013) introduce one example in the software industry, where piracy protection by the platform makes software developers better off but is against the interest of end-users who prefer free or low-cost pirate software. They argue that under certain conditions, piracy protection leads to higher profit for the platform, and the platform owner prefers to make software developers worse off to the benefit of end-users, seeking its own profit. Another example can be seen in the no-track feature of Microsoft Internet Explorer, which serves users' interests and security concerns, but reduces advertisers' access to customers' preferences (Hagiu, 2014).Search diversion is another critical trade-off that platforms need to consider.

In line with Hagiu and Julien (2011), in this paper, we call the strategy in which the platform owner harm one side's users by slowing them down and pleasing other side by giving them more exposure, as a common denomination of *waiting time increase*. Waiting time refers to the amount of time that one side's of users spend within the platform until they reach their goal which they seek from using the platform. For example, Waiting time may refer to the amount of time the consumer needs to walk in a shopping mall to find his/her preferred merchant, the amount of time a search engine user needs spends to find his/her preferred term, or the amount of time passengers spend in an airport until they catch the plane. Instead of attracting more users to the platform, increasing waiting time allows the platform owner to boost the value extraction from remaining users. The defining characteristic consists in that although one side users would prefer the platform to minimize the waiting time, the platform has the opposite incentive to increase it and harm these users to some extent. On the contrary, other side's users will benefit from having more exposure and the platform owner may extract the extra value from these users. For instance, the number of seconds of advertising that a YouTube visitor must view before being able to watch the desired video. The higher is this compulsory ad watching, the higher the waiting time, the worse-off are the visitors and the better-off are the advertisers. The decision about this amount of time, which we call waiting time, is a design strategic decision for YouTube platform.

There are many factors that influence a platform's motivation for increasing waiting time. The examples above stress profit; however, though profit is a fundamental goal for firm strategic decisions, Iansiti and Levien (2004) argue that in networked industries aggressive expropriation—what they call dominator strategy—generates unhealthy business ecosystems. For sustainability and success, firms must avoid overextraction of value and satisfy all members of the ecosystem to maintain its collective health—what they call keystone strategy. Woodard (2008) argues that where consumer tastes are unpredictable and technological development is uncertain, users are attracted to the platform that does not extract all the value that it creates. Thus, even shortsighted platform owners might have an incentive to avoid “overtaxing” their ecosystem members. Accordingly, a platform may decide to be cautious about maximizing waiting time. Accordingly platforms have an inherent tendency to please both sides of their market without overextracting one side’s value. However, this behavior may be modified when they outsource the management and development of one side to third-party firms.

Effect of outsourcing

Outsourcing is a common mean of vertical disintegration among organizations. According to Williamson (1975), firms will prefer outsourcing some of their activities as long as the cost of outsourcing to the market is lower than the cost of performing those activities in-house. Indeed, the primary driver of outsourcing is cost-reduction and enhancement of efficiency (Kakabadse and Kakabadse, 2000), though there can be other strategic reasons (Teece, 1986; Greaver, 1999).

Gawer and Cusumano (2002) propose that to sustain leadership in their ecosystems, platforms must take a coherent approach to governance systems in four distinct decisions. Among them are the choice of in-house versus outsourced activities and also the related decision about how open the platform will be to outside developers who provide goods or services.

Eisenmann, Parker, and Van Alstyne (2009) introduce four distinct players in two-sided markets: demand-side users, supply-side users (who offer complements that are used by demand-side users), platform providers (the primary point of contact between platform and users), and platform sponsors. Each platform “embodies an architecture—a design for products, services, and infrastructure facilitating network users’ interactions—plus a set of rules; that is, the protocols, rights, and pricing terms that govern transactions." (Eisenmann *et al.*, 2006: 5) The platform sponsor's role relates to these regulations and design rules. Some platforms, instead of having a direct relationship with users on both sides, may outsource the management and development of one side to third-parties. Doing so, maintaining the platform sponsor role, platform owner may contract-out the platform provider role of one side (or both) to third-parties. These third-parties would be responsible for the management, development and direct relationship with the users of that side. Outsourcing the provider role of one side allows the platform to specialize in the other side of the market and/or in sponsor role, as well as to cut costs.

To be able to motivate and keep the third-parties to play the role of platform provider on one side of the market, platform owner has to maintain the profitability of the outsourced side at a satisfactory level. Put it differently, outsourcing tilts the tendency of the platform owner to keep both sides' users pleased, toward the interest of the side that third-parties are craved to be contracted as the platform provider. Therefore, balancing the conflict of interests between the two sides, regarding the waiting time, platform owner has more tendency to harm the other side's users and increase their waiting time. Doing so, as well as yielding extra revenue, gives the third-parties more motivation to be attracted and invest on the outsourced side. Thus;

Hypothesis 1: In two-sided platforms, user waiting time increases on one side once the management of the other side is outsourced.

As a result of the higher waiting time for the in-house side, the platform becomes less attractive to this side's users. However, this strategy allows the platform to collect more revenue from the outsourced side of the market that benefits from this waiting time.

Consequently, though longer waiting time leads to loss of traffic from the users who refuse employing inefficient platform, two-sided platform compensates this loss by gaining revenue from the extra visit by the deferred users who maintain on the platform. Obviously, if the sacrificed revenue as a consequence of users decline in the in-house side is considerable, platform owner may increase waiting time just moderately to avoid the huge loss. However, this will be less likely to happen if the outsourced side is the salient source of revenue generation for the platform. In other words, According to the importance of revenue sources, the platform may choose to tilt more toward one pole or the other. Hence, prominence of one side's revenue makes traffic loss and revenue decline of (deferred) in-house side less important for two-sided platform and reinforces the platform's tendency toward increasing waiting time for the in-house side's users. Thus,

> *Hypothesis 2: In two-sided platforms, the positive effect of outsourcing on increasing waiting time for the in-house side's users will be higher when the relative revenue generated in the outsourced side increases.*

We have argued that increasing waiting time has two opposite effects for the platform: yielding additional revenue from one side, and decreasing the platform's overall attractiveness and network size. Below, we argue that concentration on outsourced and in-house sides of the platform will amplify each of these opposite effects, respectively.

Concentration on the outsourced side

As in any other market, intense competition tends to reduce the price of goods/services, while in oligopoly situation, prices are higher. Increasing waiting time boosts the potential demand for the outsourced side, and as this side becomes more concentrated, prices of goods/services provided for other side's demand rise. Consequently, any extra visit by deferred users of in-house side generates more revenue comparing to the situation in which users in outsourced side compete for other side's demand intensely. Therefore, concentration on the outsourced side amplifies the positive effect of waiting time and can compensate more for the negative effect of traffic decline.

Additionally, as the bargaining power of outsourced side increases, platform owner will be forced to please these users more while balancing the conflict of interest between two sides regarding waiting time strategic trade-off. If the outsourced side is concentrated, the bargaining power of few dominant users will be higher comparing to the fragmented case. Thus,

Hypothesis 3: In two-sided platforms, the positive effect of outsourcing on increasing waiting time for the in-house side's users will be higher when the outsourced side is more concentrated.

Concentration on the in-house side

Concentration on the in-house side has the opposite effect. As an illustration, for a business-to-business (B2B) e-commerce portal, if the buyer's side is dominated by a few big companies, slowing these buyers down may cost the platform a considerable volume of users, compared to a customer-to-customer (C2C) portal, which serves individual buyers. Bear in mind that platforms need a critical mass of users on both sides to benefit from positive indirect network effects (Evans, 2013). Undeniably, platforms can withstand network shrinkage to some extent, if this sacrifice can be offset in certain ways. However, if the shrinkage gets worse, it may cause negative feedback on the other side and, ultimately, platform collapse (Evans, 2013).Briefly, as the in-house side concentration is higher, increasing waiting time for these users will make it likelier for the platform to lose a significant portion of them all at once, and with them its attractiveness to users on the other side. Moreover, similar to the argument in outsourced side, bargaining power of in-house side increases as this side is more concentrated, which eventually force the platform owner to decrease waiting time toward their preference. Thus,

Hypothesis 4: In two-sided platforms, the positive effect of outsourcing on increasing waiting time for the in-house side's users will be lower when this side is more concentrated.

DATA, METHOD, AND RESULTS

Empirical context

The airport industry has often been seen simply as providing functional infrastructure for airlines. However, the modern airport has evolved from a "mono-modal actor" to a "multi-point firm" (Jarach, 2001: 119).Deregulation increased competition among airlines, making them more conscious of airport-related costs such as landing and passenger charges and leading to the emergence of low-cost carriers seeking low-cost airports (Barrett, 2000). In consequence, airports' airside revenue has decreased, and airport managers have been forced to look for alternative sources of revenue—most commonly, commercial revenue. Jarach (2001: 122) calls this "commercial airport" philosophy the most significant "quantum leap" in the airport industry evolution. As Gillen (2011) spells out, modern airports now obtain revenue from both airside and nonairside markets and should be considered two-sided markets with distinct but interdependent groups of customers. Airlines are better off if the airport can attract and serve more passengers. Passengers are more interested in the airports with more airline options, destinations, and flights, and commercial retailers located in the airports' terminals(such as shops, restaurants and duty-free stores) are better off if there are more airlines to bring more passengers as potential buyers. Hence, airports are two-sided (or multisided) platforms that can, for instance, reduce their landing fee to deliver shoppers to the nonairside of their market (Armstrong, 2007).

Data

To build our data set, we started by gathering longitudinal revenue data for the 150 busiest U.S. airports for six years of 2005 to 2011 from the Federal Aviation Administration (FAA) database, one of the main sources in airport studies (see, e.g., Van Dender, 2007). FAA authorization requires commercial service airports to report their financial data annually in the Compliance Activity Tracking System (CATS) report system which is publicly available for download. The reports cover aeronautical, nonaeronautical, and nonoperating revenues, operating and nonoperating expenses, net assets, capital investments, indebtedness, and the like for more than 400 U.S. airports.

Our data for dwell time, concession management structure, and details on commercial retailers come from *Airport Revenue News FactBook* (ARN FactBook),which contains various data on terminal-by-terminal and airport-wide nonaeronautical activities of the airports, complemented by some other data like dwell time, traffic, and the like for around 70 U.S. (and a few Canadian) airports, by year. This data set is one of the richest and most important data sets for studies relating to airport commercial business in the U.S. (e.g., Appold and Kasarda, 2006).

The initial data set obtained from the FAA contained 900 airport-year observations, but matching it with the ARN FactBook data reduced our final sample to 488 observations. These data are supplemented with airport traffic data from the Flight Global database. We also collected flight delay time data, aggregated by airport for each year, airlines' market share within each airport, and the city-market in which airports are located from the Bureau of Transportation Statistics, Research and Innovative Technology Administration (RITA), part of the U.S. Department of Transportation (DOT); these data are publicly available in its airline on-time performance and airport snapshot sections.

Variables

Dependent variable

Our dependent variable is *dwell time*, defined in the airport industry as the average amount of time departing passengers spend within the airport terminals in minutes. Rowley and Slack (1999: 363) recognize waiting travelers as a "lucrative source of revenue" for airports, especially in the departure lounges; and other studies have found a clear positive relationship between time of stay at the airport and consumption in the commercial area, because of boredom, the chance to spend remaining foreign currency at duty-free shops, or other reasons(Castillo-Manzana, 2010; LeighFisher and Exstare Federal Services Group LLC, 2011; Sulzmaier, 2001; Torres et al., 2005).

Passengers, of course, prefer to go quickly to the gates and spend as little as possible at the airports (Geuens, Vantomme, and Brengman, 2004). However, to avoid missing flights, they come early to the airport and usually have more time than they need for pre-boarding processes (D´Alfonso, Jiang, and Wun, 2013; LeighFisher and Exstare Federal Services Group LLC, 2011). Extra dwell time may cause them to choose another flight in another airport or not use air travel at all; for example, a significant and considerable relationship is reported between passengers' inspection time and market share of the airline industry (Holguin-Veras, Xu, and Bhat, 2012). There is thus a potential conflict of interest between airport retailers and airlines (Hanlon, 1996; Wu, 2010). Airports can manipulate waiting time by check-in procedures, security screening and passport control processes, and the like (Graham, 2008; Wu, 2010). "The adoption of such operational rules can have profound implications on how long passengers spend in the terminal." (Afshord, Mumayiz, and Wright, 2011: 427). Airports can also impact on dwell time by modifying the layout design of terminals (Forsyth et al., 2010). For example, Bristol Airport, UK, underwent a physical reorganization during 2009, as a consequence of which travelers are now forced to walk through the duty-free shop in order to get to the boarding gates (Hagiu and Julien, 2011: 355).

Since for certain years dwell time data in ARN FactBook are provided by terminal/concourse (rather than airport-wide), for those years we computed the average dwell time across terminals per airport. In our sample, there are 72 airports with more than one terminals/concourses: 12 airports with two, 18 airports with three, 10 airports with four, and 20 airports with more than four terminals/concourses. Dwell time as our independent variable is added to the model after a natural logarithmic transformation.

Independent variables

Outsourcing. Airports have various types of concession management structures for their commercial activities (LeighFisher and Exstare Federal Services Group LLC, 2011): direct leasing (the airport operator directly leases spaces to various concessionaires and oversees their use of the spaces); prime/multiple concessionaire(s) (the airport operator leases all commercial spaces to one or a few concessionaire(s), which usually operate(s) most of the spaces but may also sublet some areas); third party developer/leasing manager (the airport operator leases all commercial spaces to a specialist company that does not operate them itself but is responsible for leasing them to various individual concessionaires and managing all the spaces); and finally hybrid structures that combine some of these features. We constructed an outsourcing dummy variable (coded 0="leasing directly" or "hybrid structure," 1="otherwise") to distinguish between in-house and outsourced management of commercial activities at the airport. We use the main effect of this variable to assess Hypothesis 1 and its interaction with other dependent variables to evaluate Hypotheses 2, 3, and 4.

Commercial ratio. This variable proxies the relative prominence of revenue generated on the commercial side. It is computed as total commercial revenue divided by total operations revenue (aeronautical plus nonaeronautical) of the airport. Revenue from activities that are not directly relevant to airport business activities, such as interest income, is excluded from total operations revenue. Commercial revenue is the yearly sum of in-terminal revenues to the airport from food and beverage sales, bookstores, gift shops, duty-free shops, currency exchanges, and other in-terminal commercial activities such as telecommunications, internet access, and advertising (Fuerst, Gross, and Klose, 2011). The higher this fraction, the more incentive the airport owner has to tilt toward the commercial side's interest by increasing waiting time.

Commercial HHI. This variable proxies concentration on the commercial side of the airport and is computed as the Herfindahl-Hirschman Index of the commercial retailers in terminals when the total square footage of each tenant is taken into account. The data for commercial tenants (square feet and retailer owner) are obtained from the ARN FactBook. More specifically, the variable is computed as follows:

$$Commercial\_HHI_i = \sum_{j=1}^{n} \left({tenant\_square\_feet_j} \big/ {airport\_square\_feet_i} \right)^2$$

Airline_HHI. This variable proxies concentration on the airside. Using the DOT database, we identified the four or five airlines with the greatest numbers of passengers in each airport for each year. Again, using the Herfindahl-Hirschman Index, we compute the variable as follows:

$$Airline\_HHI_i = \sum_{j=1}^{n} \left({airline\_passenger_j} \big/ {airport\_passengers_i} \right)^2$$

Control variables

Studies show that dwell time is affected by the volume of passengers (Graham, 2009). So we include *total passengers* in thousands (after a natural logarithmic transformation) to also control for airport size. Moreover, *hub* airports' business differs somewhat from that of nonhubs; they have more transit and international passengers, and connecting time offers another opportunity to increase waiting time. Hence, we build dummy variables to distinguish among large, medium, and small hub and nonhub airports, using data obtained from the FAA website. To sort out manipulable dwell time from unexpected flight delays (which are mostly beyond the airport's control) and also to deal with potential sample selection bias (discussed later), we add a *delay time* variable (after a natural logarithmic transformation). We also control for within *city competition*, measured as the number of airport owners (from the FAA website) that serve the same city market (from the DOT website). We include the average of remaining *years to the expiry* date of the contracts with commercial retailers to control for the long-term contact which may alter platform's decision about waiting time and harming this side's users. It could be the case that airport management may increase waiting time to extract better conditions when commercial contracts are close to renewal. Finally, we also include *year* dummy variables from 2006 to 2011 to control for time-fixed effects.[13]

Descriptive statistics

Tables 1 and 2 present the descriptive statistics and correlations of the variables. Examining the bivariate correlations reveals no serious multicollinearity, other than correlations of *total passengers* with *city competition* and *commercial HHI* variables which are relatively above 0.5 and 0.6 respectively. Dealing with this and since our model contains several interactions, to avoid potential multicollinearity we mean-centered all the independent and control variables before entering them into the model. Variance inflation factors in our regressions show no evidence of severe collinearity.

[13] We exclude three serious outlier observations from our final data set.

TABLE1
Correlation matrix

Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1. Dwell time	1*						
2. Commercial ratio	0.274*						
3. Commercial HHI	-0.275*	-0.267*					
4. Airline HHI	-0.267*	-0.129*	0.252*				
5. Ln(City competition)	0.450*	0.188*	-0.315*	-0.777*			
6. Ln(Delay time)	0.130*	0.075	0.030	-0.033	0.109*		
7. Ln(Total passengers)	0.456*	0.448*	-0.614*	-0.379*	0.561*	0.111*	
8. Ln(Years to expiry)	-0.195*	-0.083	0.140*	0.212*	-0.318*	-0.094	-0.226*

N=240, All correlations with asterisk are significant at the .05 level.

TABLE 2
Descriptive statistics

Variables	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Dwell time	282	4.312	0.387	3.219	5.124
Commercial ratio	484	0.120	0.058	0.016	0.359
Commercial HHI	476	0.584	0.274	0.066	1.000
Airline HHI	485	0.839	0.239	0.249	1.000
Ln(City competition)	485	0.544	0.598	0.000	1.609
Ln(Delay time)	474	2.422	0.219	1.767	3.109
Ln(Total passengers)	479	15.963	1.224	12.874	18.342
Ln(Years to expiry)	417	1.529	0.629	-0.095	3.125

Results

Table 3 shows the results of an OLS regression with robust standard errors to heteroskedasticity. Model 1 contains only the control variables. Model 2 adds the outsourcing dummy; models 3, 4, and 5 interactions with commercial ratio, commercial HHI, and airline HHI, respectively. Finally, Model 6 incorporates all the variables.

Model 2 shows no significant effect of *outsourcing* on *dwell time* (β= -.014, $p>0.1$) and thus shows no support for Hypothesis 1. However, Hypothesis 2 predicts a positive coefficient for the interaction of outsourcing and commercial ratio, and Model 3 shows adequate support for this expectation (β= 1.155, $p<0.1$). In line with Hypothesis 3, Model

4 shows a positive interaction between *outsourcing* and *commercial HHI* that is significant at the 10% level (β= 0.333, p<0.1). Hypothesis 4 predicts a negative moderation effect for concentration on the other side of the market (computed by *airline HHI*). Model 5 rejects this hypothesis: the interaction coefficient is significantly positive (β= 0.534, p<0.05), therefore, rejecting Hypothesis 4.

In general, Model 6 supports Hypotheses 2 and 3 strongly, even at higher significance levels than earlier models (β= 1.556, p<0.05; β= 0.405, p<0.05). For Hypothesis 1 we do not have enough support and Hypothesis 4 is rejected.

TABLE 3
Ln(Dwell time)

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Outsourcing		-0.014	-0.028	-0.018	-0.008	-0.028
		(0.047)	(0.046)	(0.047)	(0.047)	(0.046)
Commercial ratio			0.350			0.134
			(0.408)			(0.393)
Commercial ratio × outsourcing			1.155+			1.556*
			(0.627)			(0.646)
Commercial HHI				-0.146		-0.210
				(0.136)		(0.133)
Commercial HHI × outsourcing				0.333+		0.405*
				(0.177)		(0.169)
Airline HHI					-0.448*	-0.456*
					(0.197)	(0.189)
Airline HHI × outsourcing					0.534*	0.445+
					(0.235)	(0.226)
Ln(City competition)	0.159***	0.159***	0.173***	0.166***	0.185***	0.208***
	(0.040)	(0.040)	(0.042)	(0.039)	(0.042)	(0.044)
Ln(Delay time)	-0.227*	-0.224*	-0.214*	-0.274**	-0.221*	-0.247*
	(0.100)	(0.102)	(0.103)	(0.100)	(0.106)	(0.107)
Ln(Total passengers)	0.083+	0.079+	0.073+	0.060	0.062	0.030
	(0.042)	(0.041)	(0.041)	(0.044)	(0.045)	(0.044)
Ln(Years to expiry)	0.007	0.007	-0.001	0.000	0.020	-0.001
	(0.036)	(0.036)	(0.035)	(0.036)	(0.040)	(0.038)
Year dummies	YES	YES	YES	YES	YES	YES
Hub status dummies	YES	YES	YES	YES	YES	YES
Constant	4.995***	4.986***	5.013***	4.991***	4.949***	4.963***
	(0.197)	(0.195)	(0.202)	(0.192)	(0.211)	(0.210)
Observations	240	240	240	240	240	240
R^2	0.300	0.301	0.316	0.312	0.320	0.350
Adjusted R^2	0.263	0.260	0.270	0.266	0.275	0.294

Standard errors in parentheses, +*p*< 0.10, * *p*< 0.05, ** *p*< 0.01, *** *p*< 0.001.
All models are OLS regressions with robust standard errors.

Interestingly, although hub status is not related to our hypotheses, in the vast majority of the models hub dummy variables (large/medium/small) have negative coefficients, which are significant in various models. We may interpret this as an essential difference between hub and nonhub airports: hub airports can manipulate connecting time between two flights for transfer passengers in addition to dwell time, so that, other things being equal, we may expect shorter dwell time for hub airports because they can compensate for the short dwell time with longer connecting time.

Robustness tests

Arguably, increasing dwell time (our dependent variable) might increase commercial revenue and thus commercial ratio (one of our independent variables). Therefore, our results may suffer from reverse causality. To rule out this possibility, we replace commercial ratio in the model with the lagged (previous year) value and rerun the mentioned OLS models. The outputs appear in Table 4.

TABLE 4
Ln(Dwell time)- Lagged version

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Outsourcing		-0.014	-0.019	-0.018	-0.008	-0.020
		(0.047)	(0.047)	(0.047)	(0.047)	(0.047)
Commercial ratio			0.080			-0.160
			(0.397)			(0.377)
Commercial ratio × outsourcing			0.672			1.146+
			(0.617)			(0.663)
Commercial HHI				-0.146		-0.191
				(0.136)		(0.134)
Commercial HHI × outsourcing				0.333+		0.403*
				(0.177)		(0.172)
Airline HHI					-0.448*	-0.464*
					(0.197)	(0.191)
Airline HHI × outsourcing		-0.014	-0.019	-0.018	-0.008	-0.020
		(0.047)	(0.047)	(0.047)	(0.047)	(0.047)
Ln(City competition)	0.159***	0.159***	0.163***	0.166***	0.185***	0.197***
	(0.040)	(0.040)	(0.042)	(0.039)	(0.042)	(0.044)
Ln(Delay time)	-0.227*	-0.224*	-0.214*	-0.274**	-0.221*	-0.244*
	(0.100)	(0.102)	(0.103)	(0.100)	(0.106)	(0.107)
Ln(Total passengers)	0.083+	0.079+	0.077+	0.060	0.062	0.036
	(0.042)	(0.041)	(0.040)	(0.044)	(0.045)	(0.045)
Ln(Years to expiry)	0.007	0.007	0.007	0.000	0.020	0.007
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Year dummies	YES	YES	YES	YES	YES	YES
Hub status dummies	YES	YES	YES	YES	YES	YES
Constant	4.995***	4.986***	4.999***	4.991***	4.949***	4.946***
	(0.197)	(0.195)	(0.200)	(0.192)	(0.211)	(0.208)
Observations	240	240	240	240	240	240
R^2	0.300	0.301	0.304	0.312	0.320	0.338
Adjusted R^2	0.263	0.260	0.258	0.266	0.275	0.281

Standard errors in parentheses, +p< 0.10, * p< 0.05, ** p< 0.01, *** p< 0.001.
All models are OLS regressions with robust standard errors.

Table 4's final model demonstrates a similar pattern to our original (unlagged) model, giving us enough confidence to rule out the reverse causality bias.

To address this potential endogeneity problem further, we apply a Generalized Method of Moments (GMM) estimator. More precisely, we include lagged variables of the regressors as instrumental variables in the model. We use different specifications of GMM for our final model, and the results are displayed in Table 5. Model 1 contains original and one-year lagged versions of all regressors (except dummy variables) as instrumental variables. Similarly, Models 2 and 3 add up to second-year lagged version and all available lagged versions to the instruments set, respectively. A Hansen test for overidentification shows that J statistics are not significant even at 10% in all models and that we cannot reject the validity of overidentification restrictions (Hansen, 1982); therefore, no models are misspecified. All Models 1, 2 and 3 confirm Hypotheses 2 and 3 strongly, show no support for Hypothesis 1 and reject Hypothesis 4. However, only Model 3 shows no evidence of support for the last hypothesis. Thus, according to both GMM and OLS with lagged variable outcomes in Tables 4 and 5, we can be confident that our results are not biased by endogeneity.

TABLE 5
Ln(Dwell time)- GMM analysis

Variables	**Model 1**	**Model 2**	**Model 3**
Outsourcing	-0.044	0.034	-0.039
	(0.030)	(0.046)	(0.064)
Commercial ratio	-0.031	-0.308	-0.244
	(0.321)	(0.643)	(0.616)
Commercial ratio × outsourcing	2.235**	2.325*	2.103**
	(0.734)	(1.091)	(0.750)
Commercial HHI	-0.221***	-0.275**	-0.251**
	(0.058)	(0.087)	(0.094)
Commercial HHI × outsourcing	0.503***	0.546***	0.483***
	(0.087)	(0.135)	(0.131)
Airline HHI	-0.497***	-0.510**	-0.415*
	(0.133)	(0.158)	(0.192)
Airline HHI × outsourcing	0.442**	0.453*	0.350
	(0.155)	(0.202)	(0.217)
Ln(City competition)	0.247***	0.273***	0.216***
	(0.031)	(0.033)	(0.035)
Ln(Delay time)	-0.181**	-0.263**	-0.236*
	(0.065)	(0.102)	(0.093)
Ln(Total passengers)	0.017	0.063	0.064
	(0.042)	(0.060)	(0.074)
Ln(Years to expiry)	-0.005	0.008	-0.013
	(0.020)	(0.027)	(0.027)
Year dummies	YES	YES	YES
Hub status dummies	YES	YES	YES
Constant	4.885***	5.150***	5.053***
	(0.188)	(0.277)	(0.245)
Observations	240	240	240
Hansen's J Chi-square	45.69	40.45	38.98
p-value	0.21	0.41	0.47

Robust standard errors in parentheses, +$p< 0.10$, * $p< 0.05$, ** $p< 0.01$, *** $p< 0.001$.

A second problem is that in our data more than 200 airport-year observations are missing for our dependent variable. This makes us suspect that our model may suffer from sample selection bias, meaning that airports intentionally avoid reporting their dwell time to ARN FactBook. Especially, it is conceivable that airports with long delays prefer to keep their dwell time unreported to protect their reputations. To deal with this problem we use a Heckman selection model (Heckman, 1979). This model includes two equations: the first stage estimates a probit regression in which the dependent variable is a dummy equal to one if the airport reports its dwelling time and zero otherwise. The second stage includes the inverse of the Mills ratio in our main regression to control for self-selection. (Heckman, 1979; Greene, 2003).We construct our first-stage selection model without exclusion restrictions (Cameron and Trivedi, 2009), meaning that all independent and control variables in the outcome model are considered as explanatory variables in the probit. The results of the two-stage Heckman model are shown in Table 6.

TABLE 6
Ln(Dwell time)- Two-step Heckman model

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
2nd stage:						
Outsourcing		-0.049	-0.041	-0.094	-0.061	-0.079
		(0.085)	(0.077)	(0.116)	(0.093)	(0.095)
Commercial ratio			0.388			0.201
			(0.540)			(0.567)
Commercial ratio × outsourcing			1.231			1.959+
			(0.895)			(1.111)
Commercial HHI				-0.315		-0.326
				(0.274)		(0.234)
Commercial HHI × outsourcing				0.444+		0.485*
				(0.251)		(0.224)
Airline HHI					-0.383+	-0.413*
					(0.223)	(0.201)
Airline HHI × outsourcing					0.544+	0.466+
					(0.280)	(0.267)
Ln(City competition)	0.167**	0.140*	0.168**	0.131+	0.152*	0.186**
	(0.056)	(0.061)	(0.053)	(0.073)	(0.071)	(0.062)
Ln(Delay time)	-0.129	-0.420	-0.281	-0.631	-0.517	-0.473
	(0.444)	(0.413)	(0.349)	(0.494)	(0.451)	(0.384)
Ln(Total passengers)	0.103	0.034	0.058	-0.058	-0.003	-0.042
	(0.103)	(0.107)	(0.093)	(0.169)	(0.113)	(0.130)
Ln(Years to expiry)	0.020	-0.017	-0.009	-0.049	-0.013	-0.029
	(0.068)	(0.062)	(0.054)	(0.081)	(0.066)	(0.062)
Year dummies	YES	YES	YES	YES	YES	YES
Hub status dummies	YES	YES	YES	YES	YES	YES
Constant	5.051***	4.866***	4.975***	4.739***	4.784***	4.834***
	(0.322)	(0.330)	(0.273)	(0.429)	(0.346)	(0.310)
1st stage:						
Outsourcing		-0.270+	-0.286*	-0.314*	-0.278*	-0.335*
		(0.140)	(0.142)	(0.142)	(0.141)	(0.144)
Commercial ratio			0.801			0.303
			(1.616)			(1.651)
Commercial ratio × outsourcing			1.719			2.702
			(2.574)			(2.659)
Commercial HHI				-0.654		-0.723+
				(0.427)		(0.433)
Commercial HHI × outsourcing				0.442		0.526
				(0.525)		(0.543)
Airline HHI					0.383	0.325
					(0.533)	(0.540)
Airline HHI × outsourcing					0.033	0.096
					(0.757)	(0.766)
Ln(City competition)	-0.125	-0.145	-0.124	-0.143	-0.175	-0.152
	(0.140)	(0.141)	(0.143)	(0.143)	(0.145)	(0.148)
Ln(Delay time)	-1.583***	-1.539***	-1.514***	-1.492***	-1.594***	-1.517***
	(0.365)	(0.366)	(0.368)	(0.377)	(0.374)	(0.384)
Ln(Total passengers)	-0.321+	-0.340*	-0.339*	-0.454**	-0.330*	-0.441*
	(0.167)	(0.167)	(0.170)	(0.175)	(0.168)	(0.178)
Ln(Years to expiry)	-0.219+	-0.192+	-0.189	-0.207+	-0.177	-0.190
	(0.115)	(0.115)	(0.116)	(0.117)	(0.118)	(0.121)
Year dummies	YES	YES	YES	YES	YES	YES
Hub status dummies	YES	YES	YES	YES	YES	YES
Constant	5.735***	5.918***	6.107***	5.744***	6.017***	6.053***
	(0.289)	(0.292)	(0.295)	(0.295)	(0.295)	(0.301)
Mills Lambda	-0.118	0.242	0.085	0.458	0.358	0.290
	(0.513)	(0.485)	(0.413)	(0.598)	(0.518)	(0.461)
Observations	405	405	405	403	405	403

Standard errors in parentheses, +*p*< 0.10, * *p*< 0.05, ** *p*< 0.01, *** *p*< 0.001.

The results in the final model (Model 6) show support for Hypotheses 2 and 3, but there is not enough confirmation for hypotheses 1 and 4. However, though we have significant coefficients in the selection stage, especially a negative sign for the delay coefficient as we expected, the inverse Mills ratios in our two-step Heckman models are not significant at the 10% level. Thus, it can be claimed that sample selection bias is not an issue in our OLS results.

Furthermore, in building our outsourcing dummy variable, we assumed that hybrid structures involved some in-house management. But a hybrid structure might combine a prime/multiple concessionaire(s) and a third-party developer/leasing manager, and such a combination would have to be considered as an outsourcing case. Therefore combining hybrid structures with direct leasing may not be an appropriate measure in all cases. Unfortunately, the ARN FactBook data do not provide detailed information about hybrid structure. However, in LeighFisher and Exstare Federal Services Group LLC (2011), a comprehensive manual for airport in-terminal commercial activities, almost all the cases reported for hybrid structure show that direct leasing is part of the commercial contract. We have tried to supplement these data on hybrid structure with the contact information provided in ARN FactBook for each airport to see whether the airport's owner is also included in concession management contacts, and with information from airport owners' websites. We have become fairly confident that hybrid structure should be categorized together with direct leasing as (full or partial) in-house management of the commercial side. Furthermore, rerunning the regressions by converting the outsourcing dummy variable to one for cases of hybrid structure that may evidence outsourcing also shows a similar pattern to the original result described above. The results of above robustness analyses are not reported, but available upon request.

Finally, one could argue that passengers who travel with low-cost carriers (LCC) have different consumption behavior in terminals than legacy airline travelers. This difference may affect the waiting time strategy of the airports with a high percentage of LCC passengers. Previous studies have documented that low-cost carriers prefer to serve nonhub airports generally, and to avoid the large hubs (Ito and Lee, 2003). Hence, we have already captured this difference by the airports´ hub status as a control variable. Moreover, after extracting additional data about LCC penetration (the percentage of LCC traffic to the total traffic per airport) and including it in our models, the results are corroborative in the final model—with all interactions included. As mentioned in the outset, the presence of transit passengers, as captive travelers in terminals, offer an extra opportunity of manipulating connecting time for the airports, in addition to increasing waiting time. Hence, it could alter their waiting time strategy. Flight Global dataset covers data about the percentage of transit to total passengers. However, this variable equals to zero for more than fifty percent of the observations in the dataset, which makes the accuracy of the data questionable. Although we have already captured the impact of this variable by hub status of the airports, after incorporating this variable as an additional control the statistical significance of the results is weakened, but they are still supportive. Table 7 displays the results after including two abovementioned variables (mean centered) in the control set[14].

[14] Also, as the most conservative approach the standard errors here are clustered at airport level.

TABLE 7
Ln(Dwell time)

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Outsourcing		0.010	-0.004	0.007	0.032	0.012
		(0.074)	(0.073)	(0.073)	(0.074)	(0.072)
Commercial ratio			0.559			0.474
			(0.627)			(0.503)
Commercial ratio × outsourcing			1.045			1.446+
			(0.828)			(0.760)
Commercial HHI				-0.175		-0.250
				(0.205)		(0.175)
Commercial HHI × outsourcing				0.363		0.442+
				(0.245)		(0.223)
Airline HHI					-0.831*	-0.868*
					(0.363)	(0.342)
Airline HHI × outsourcing					0.801*	0.725+
					(0.388)	(0.374)
Ln(City competition)	0.129+	0.129+	0.146+	0.139*	0.153*	0.185**
	(0.070)	(0.070)	(0.073)	(0.065)	(0.066)	(0.064)
Ln(Delay time)	-0.227	-0.229	-0.223	-0.273+	-0.230	-0.259+
	(0.165)	(0.169)	(0.168)	(0.158)	(0.163)	(0.152)
Ln(Total passengers)	0.098	0.101	0.094	0.076	0.091	0.049
	(0.081)	(0.073)	(0.073)	(0.073)	(0.074)	(0.070)
Ln(Years to expiry)	0.001	0.001	-0.009	-0.007	0.011	-0.015
	(0.052)	(0.051)	(0.050)	(0.050)	(0.057)	(0.050)
LCC penetration	0.063	0.062	0.069	0.026	0.237*	0.237*
	(0.142)	(0.142)	(0.143)	(0.132)	(0.111)	(0.112)
Transit to total passengers%	6.922	7.029	7.596+	7.382+	11.239***	12.452***
	(4.235)	(4.268)	(4.352)	(4.294)	(3.213)	(3.209)
Year dummies	YES	YES	YES	YES	YES	YES
Hub status dummies	YES	YES	YES	YES	YES	YES
Constant	4.393***	4.386***	4.372***	4.411***	4.433***	4.449***
	(0.129)	(0.115)	(0.120)	(0.116)	(0.109)	(0.109)
Observations	240	240	240	240	240	240
R^2	0.325	0.325	0.344	0.338	0.375	0.414
Adjusted R^2	0.283	0.280	0.293	0.287	0.327	0.358

Standard errors in parentheses, +*p*< 0.10, * *p*< 0.05, ** *p*< 0.01, *** *p*< 0.001.
All models are OLS regressions with clustered (by airport) robust standard errors.

DISCUSSION

This paper introduces the waiting time concept in two-sided platforms and studies the factors that motivate two-sided platforms to increase waiting time for one side of the market. We find that platforms, once outsource the management of one side of the market, are more prone to increase waiting time for other side's users, the higher is the prominence of revenue generation and/or concentration is in outsourced side.

We did not find enough evidence to confirm the first hypothesis: tendency for increasing waiting time is higher once we witness outsourcing the provider role in one side of the platform. However, the insignificant result for this hypothesis attest that outsourcing *per se* does not suffice to bring enough interest for the platform owner for harming users in one side. Some additional factors as hypothesized in second and third hypotheses has to be present to strengthen the positive effect of waiting time, in comparison with the negative impact of traffic decline.

We also found opposite result to the fourth hypothesis. We claim that this may relates to the contextual conditions. Passengers may benefit from concentrated airlines in some ways; for instance, more frequent flights and wider hour schedule with the same airline, which leads to lower search cost for travel planning. Having this opportunity, they may care less to the harm of dwell time which justifies higher waiting time strategy of the airport owner. Moreover, it is well documented that highly concentrated airports by few dominant airlines are the source of above average ticket fare, which is called airline's hub-premium (Borenstein, 1989). Hence, dominant airlines also can compensate the harm of waiting time (probably passengers decline) by higher ticket fare and will be more tolerable to the increase of waiting time.

Our study's contribution to both theory and practice is manifold. First, this study scrutinizes the novel concept of waiting time in two-sided platforms. Despite being almost untouched in the literature, this strategy is widespread in network industries, this is true both in traditional sectors such as magazines and shopping malls and in more high-tech businesses like search engines and e-commerce portals. We allege that two-sided platforms can increase waiting time on one side and make these users worse off, while pleasing the other side users which are an eminent source of revenue for the platform. Put differently, including some noise to the interaction of users, although makes the platform under-optimized and less-efficient for deterred users, it opens up the possibility of serendipitous interactions, which provides higher visibility for other side users and revenue generation for the platform. This phenomenon is interesting by itself; despite the praise of common wisdom in favor of perfection and efficiency, indirect network effect allows the platforms to make advantage of some degrees of slowness and under-optimization to manipulate different sides' demand and utility, and boost its profit. In this case, perfect is not always good, and the platform is better off once includes some ingredients of dullness and delay to its design. Undeniably, platforms have to take into account different factors while implementing this strategy, some of which are discussed in our paper. Rooted in search diversion's economic model proposed by Hagiu and Jullien (2011, 2013), to our knowledge our paper is the first one that inquires this phenomenon and its contingencies in management literature theoretically and examines it empirically.

Second, our paper contributes to platforms design and architecture literature. Most of previous studies mostly focused solely on pricing strategies for platforms and with few exceptions neglect the richer picture of how platforms can improve its ecosystem profitability and health (Iansiti & Levien, 2004). Pricing system is not a sufficient instrument for two-sided platform to maximize its performance while nonprice strategies are able to solve the so-called "two-sided market failure" arising from over-emphasizing on price structure (Boudreau and Hagiu, 2009). We show in our study that instead of just concentrating on subsidizing one side and monetizing other and trying to amass their user base, platforms by a deliberated and subtle design (as a nonpricing instrument) can resonate their revenue higher, even at the expense of total users decline. As mentioned before, the instances of this sort of design and architecture in the real world are far-reaching including magazines' layout, shopping malls' arrangement, e-commerce websites' search algorithm, airports' in-terminal dwell time/connecting time manipulation and the like.

Finally, in the realm of empirical analysis, despite the call for rethinking airport industry from multisided platform perspective (Gillen, 2011) to avoid fallacies of one-sided logic in multi-sided markets (Wright, 2004) there is a considerable negligence in this regard. Our study is among the first ones along with few exceptions to our knowledge (Gillen, 2011; Ivaldi, Sokullu, and Toru, 2011; Malavolti, 2010) to scrutinize airports from a two-sided approach. Especially dwell time factor in the airport industry provide an accurately measurable and appropriate proxy for waiting time in our arguments which make airports even more interesting as our empirical context.

Limitations and further research

Like any other study, this one is not without limitations. However, these shortcomings can open opportunities to be pursued and may spur others to further this research. While airport industry is interesting enough to be studied from two-sided lens, future researches can investigate the extent to which our framework holds in other industries. Although ARN FactBook data is one the most comprehensive databases for US airports' commercial business, it suffers from considerable missing data for our dependent variable. Moreover, dwell time data seemingly includes both waiting time in security checks and free time for shopping in the terminals, though roughly 90% of dwell time is devoted to the latter (Appold and Kasarda, 2006) refining this data as well as compensating the missing ones from complementary databases may gain better results. Furthermore, the hybrid structure of commercial contract may be investigated with more scrutiny by other sources if available, to give more confidence about combining it with direct leasing structure, as we described earlier. Regarding Hypothesis 4, the results have to be considered cautiously and need further investigations in other context and/or controlling for more parameters by expanding the available data.

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Chapter Three

Stock versus Novelty: Technology Adoption Momentum Revisited

INTRODUCTION

The theory of momentum (and associated concept of inertia) (Arthur, 1989; Besen and Farrell, 1994; Katz and Shapiro, 1986, 1992, 1994; Shapiro and Varian, 1999) has been very influential in work assessing technology adoption decisions, as shown by the extensive number of studies employing the concept to explain why a given technology wins over competing alternatives or fails to gain users. Especially in contexts characterized by network externalities, it is commonly understood that building momentum around a technology to reach quickly a critical mass of users is paramount for success, as existing users attract new users through a self-reinforcing effect (e.g., Arthur, 1989; Hill, 1997). Because of this inertial force, the technology with the larger network will eventually become the dominant standard or platform and win the entire market (e.g., Arthur 1996; Evans, 2003).

However, particularly in recent years, and for platform technologies, we do observe tremendous changes in leadership across different sectors, from social networks (e.g., Facebook, Twitter) to mobile computing (e.g., Apple iOs, Google Android) or media and entertainment systems (e.g., YouTube, Microsoft's Xbox), with new entrants dethroning incumbents despite their large networks, and promising technologies losing momentum despite initial critical mass of users (e.g., Blackberry). Prior studies have acknowledged these possibilities; in fact, the logic of inertia has been used to explain success as well as failure cases (e.g., Evans and Schmalensee, 2010; Katz and Shapiro, 1994, Ozalp and Cennamo, 2015; Schilling, 2002). The theory equally fits the resulting equilibrium outcome of technologies that gain market dominance, and those that never reach a critical mass of users. This leads to theory's predictions that are ambiguous, as first acknowledged by Arthur (1989), who stressed the importance of contingent, historical events in shaping inertia towards motion or stasis, and more recently by Argyres, Bigelow, and Nickerson (2015) who advanced the idea of “innovation shocks.” Missing is an understanding of the dynamic aspect of momentum: what does cause a technology to sustain or lose momentum over time?

In this study, we address this question conceptually, by revisiting the concept of momentum into inertial *and* dynamic components, and empirically, by estimating the effects of both components on technology/platform adoption in a context with indirect network externalities. Drawing from Physics literature that defines momentum as the product of an object’s mass and its velocity (Halliday, Resnick, and Walker, 2010), we conceptualize the inertial component of momentum (i.e., mass) as the *cumulative* network size of a technology at a given point in time, and the dynamic component (i.e., velocity) as the *change* in network size from previous period at a given point in time. More precisely, applied to a platform technology context, we assess the effect of the cumulative number of complements available for a platform at time t-1, and the effect of the change in such number between time t and t-1 on platform adoption at time t. We refer to these effects as *stock* and *novelty* effects respectively.

In line with the idea that momentum is determined, and sustained over time, by both the mass (inertial effect) and velocity (dynamic effect), we advance that novelty has a positive effect on platform adoption, controlling for the effect of stock of complements, and that this effect is stronger (in magnitude terms) relative to the effect that stock has on platform adoption. We then consider the effect of momentum at the aggregate level – all platforms belonging to the same technology generation. We argue that the point when the mass of users in the market switch/adopt the given generation (i.e., the market tipping point) coincides with the period when the pondered average of the novelty of all platforms of same technological generation peaks. Empirical analysis of multiple platforms across distinct time periods and technological generations in the U.S. video game industry brings supporting evidence to these predictions, with results that are robust to different model specifications and alternative operationalization.

In revisiting the concept of momentum, we contribute to the literature on technology adoption by integrating the existing theoretical focus and much of the empirical inquiry on inertia with the dynamic aspect. Coupling the inertial and dynamic elements of momentum can offer a better way to elucidate on the evolutionary trajectory of a technology, also, and relevantly, in relation to other competing technologies. If one also accounts for velocity (i.e., dynamic effect) and not just mass (i.e., inertial effect) of a technology's momentum over time, it becomes apparent, for instance, that reaching a "critical mass" may not be a necessary condition for winning the whole market: a new technology with a small mass but high velocity might soon catch up on the incumbent's user base, or eventually co-exist in the market. We also extend the literature by conceptually articulating on and empirically showing when the market will "tip" at the aggregate level (for a given technology generation).

Finally, we contribute to the growing literature of two-sided platform competition by empirically documenting that complement novelty impacts platform adoption by users much more than the stock of available complements—this has relevant implications for the characterization of network effects and competitive dynamics. We try to advance the discussion beyond the current "size" characterization of indirect network effects.

THEORETICAL BACKGROUND

The concept of inertia and momentum in technology adoption studies

It has been well established in the extensive literature of technology adoption that a single technology tends to corner the market and become the dominant "design", "standard", or "system" (e.g., Farrell and Klemperer, 2007; Hills, 1997; Katz and Shapiro, 1986, 1992; 1994; Suarez and Utterback, 1995). Studies commonly refer to the point at which one technology stands out of the crowd and gains wide adoption while locking out other, competing technologies, as the market tipping point[15] (e.g., Besen and Farell, 1994; Katz and Shapiro, 1994; Shapiro and Varian, 1999). Although the dominant technology is not necessarily the best and most advanced one, market tipping is considered as a guarantee for the success of the technology against extant rivals or new entrants. Studies on technology adoption allege that being adopted by a large amount of consumers has a self-reinforcing effect. This effect could be either because of increasing returns to technology—the more they are adopted, the more experience and improvement is attained—(Arthur, 1989; Hills, 1997), or as a consequence of social bandwagon effects and/or reputation—existing customers elicit more customers (David and Greenstein, 1990; Katz and Shapiro, 1994; Suarez, 2005; Wade, 1995).

The presence of network externalities makes this effect more acute. In particular, in industries characterized by direct network effects, consumers value the product more if used by more consumers; thus, the technology with the largest number of users will

[15] See Katz and Shapiro (1994) for more studies documenting the tipping point phenomenon in different industries.

become progressively more attractive to new users and induce greater adoption (Arthur, 1983; Church and Gandal, 1996; David, 1985). Similarly, when indirect network externalities exist (Farrel and Klemperer, 2002; Katz and Shapiro, 1985), the number of consumers and available complementary goods of a platform generate a positive feedback that enables the platform to grow rapidly and become the market leader—that is, the winner-takes-all outcome (Arthur 1996; Evans, 2003; Gawer and Cusumano, 2008; Kelly 1998; Rochet and Tirole, 2003).

Katz and Shapiro (1992) in their seminal paper distinguish two situations. First, the case of *excess inertia* in which an incumbent technology with a large installed base of users penetrates the mass market and does not leave any room for other incompatible technologies to survive. In other words, customers are (positively) biased towards the incumbent and large technology, and it prevents them from switching to new technologies, even when the latter offer better functionalities. Second, in the opposite case of *insufficient friction*, the new technology with smaller installed base may take over the market—that is, the friction is not sufficient to entrap the customers in using the old technology. Indeed, previous studies have acknowledged the possibility of multiple equilibria (e.g., Arthur, 1989; Economides and Himmelberg, 1995; Katz and Shapiro, 1985). Yet, most of them tend to support the idea that the market eventually converges to a single dominant technology because of excess inertia. Arthur (1989), for instance, demonstrates how small changes in initial conditions cause one of the feasible equilibria to be realized. Consistently, more recent studies highlight the aforementioned self-reinforcing effect, stating that once a technology and/or platform gains enough number of users and complementary goods—the *critical mass*—it ignites; that is, it gains market *momentum* until a stable equilibrium (e.g., Evans, 2009; Lee, Lee, and Lee, 2003; Rogers, 2003). Differently, when the critical mass is not reached, momentum fades off and the technology eventually gets locked out the market (Schilling, 2002). Accordingly, amassing user base snowballs the growth of the technology and leaves rivals behind. The network size (i.e., installed base of users and variety of complementary goods) is vastly considered as of critical importance for the success of a technology/platform and its dominance in the market.

Arthur (1989) acknowledged long ago that the dynamics of increasing returns to technology adoption and historical events are of much importance to predict the market outcome. Notwithstanding, in our opinion, much of the focus in previous studies has remained on the notion of excess inertia and in a static framework, while overlooking the dynamics of insufficient friction arguments raised by Katz and Shapiro (1992; 1994). Existing literature does not adequately explain why some new entrants are able to dethrone the incumbent technology/platform (Suarez and Kirtley, 2012). Schilling (2002), instead, shows that technology selection possesses a nonlinear and path-dependent character. The timing of entry has a U-shape effect on the chance of technology dominance; hence, both entering very early or very late to the market increases the likelihood of being locked out. Other studies also criticize the emphasis on the size of the installed base and highlight other factors that are of importance in addition to network size such as quality, consumers' expectation, and network's composition (Lee, Lee, and Lee, 2006; Shankar and Bayus, 2003; Suarez, 2005; Zhu and Iansiti, 2012). For instance, Zhu and Iansiti (2012:95) depict the situations whereby "consumers care about new applications to be released in the near future in addition to the currently available ones."

Moreover, and most importantly, previous research has conceptualized momentum mainly from a static point of view. Table 1 shows a brief review of definition and operationalization of momentum/inertia in key technology adoption papers. Most of these studies tend to implicitly conflate the notion of momentum with the actual installed user base, thus, considering *de facto* only the *inertial* component of the momentum—that is, the accumulated size of user base at each frame of the motion. Although most of this work is motivated by the objective to explain the evolution of technologies through the course of time, most of the studies limits the lens to the initial phase of the “takeoff” and assumes persistence, stability, and stasis for the rest of the movement. Less explored, particularly at the empirical level, is the *dynamic* aspect of motion: how the change and fluctuation of the mass of users/complements affects the evolutionary dynamics of technology adoption.

TABLE 1
Definition of inertia/momentum in the extant literature

Source	***Notion of momentum***	***Operationalization***
Arthur, 1989	“[T]he more they [i.e. the technologies] are adopted, the more experience is gained with them, and the more they are improved. It may therefore become further adopted and further improved.”	Formal modeling paper
Hills, 1997	Self-reinforcing relationship between value to customers and installed base	Conceptual paper
Katz and Shapiro, 1986	“A given product is more attractive the larger is in-place base of consumers using the product.”	Formal modeling paper

Katz and Shapiro, 1992, 1994	Tendency of users to stick with the established technology with large network size and avoiding adoption of new technologies	Formal modeling and conceptual papers
Schilling, 2002	The size of the installed base and the availability of complementary goods reinforce each other	Number of users and range of complementary products and/or services for use with your product
Schilling, 2003	size of installed base of users and availability of complementary products	No details available (descriptive paper)
Lee et. al., 2006	Size of installed base of users as well as local bias between users determines the winner-takes-all outcome.	Simulation paper
Evans, 2009	"Multi-sided platforms often must attain critical mass to ignite a catalytic reaction that leads to organic growth. Platforms that do not reach this critical mass implode."	Conceptual paper
Evans and Schmalensee, 2010	"[F]or any given price and non-price policy, if a potentially viable business attains a critical mass of participants, network effects will drive subsequent growth until the business reaches a stable equilibrium."	Formal modeling paper
Suarez and Kirtley, 2012	"The size of the installed base becomes a key factor in the demand for a product or service, often more important than price or quality. Building a large installed base can seem like an insurmountable obstacle for platform challengers."	Conceptual paper
Evans, 2013	"[O]nce a platform reaches critical mass, it "ignites" in the sense that it is propelled forward by its own momentum from positive-feedback effects."	Conceptual paper

From stasis to dynamic motion

Jansen (2004) hints similar distinction between static and dynamic views of momentum in organizational change studies. In this strand of research, momentum is considered as a significant factor of change. However, Jansen argues, the majority of papers has investigated it more as a static phenomenon and adopted an inertial conceptualization. He distinguishes static-based momentum from change-based momentum. The former is associated to persistence to the current trajectory or incremental changes, while the latter explains pursuit of a new trajectory and frame-breaking change. In his words, static-based momentum describes "the energy associated with persisting with or extending the current trajectory" [i.e., inertia], whereas change-based momentum describes the "energy associated with pursuing a new trajectory" (Jansen, 2004: 277). Nevertheless, this distinction is not convincing as what Jansen refers to as dynamic, the changed-based momentum, retains a great part of the inertial conceptualization indeed, as also the "new" trajectory consists in *repetitive persistence* in routines, albeit new ones.

Nevertheless, the point raised by Jansen, the distinction between the static and dynamic components of momentum, is a vital one if we were to move past the inertia metaphor and fully appreciate how momentum affects the evolution of the "it" at study (be it organizational routines or technology adoption). This is particularly relevant for technology adoption in the presence of network effects. Restricting focus to the static view of momentum and, thus, mainly on total network size prevents us from fully capturing the dynamism of battles among technologies, and explaining why in some situations new technologies quickly outperform the big and long lasting incumbents. In fact, some authors have used insights from other theories such as social networks or institutional isomorphism (e.g., Suarez, 2005; Wade, 1995) to explain these situations. The examples of these *platform dethroners*—late comers, yet key players of the market— are prevalent in different industries (Suarez and Kirtley, 2012). Also, since the inertia logic implies that later entrants will lag behind in network size vis-à-vis early entrants and can barely survive, many of the previous studies are mainly concerned with factors affecting first mover dis/advantage at the time of entry, but miss to explore how the temporal development of the market and technology affects this dis/advantage (Suarez and Lanzolla, 2007). Empirical work by Christensen, Suarez, and Utterback (1998) and Schilling (2002) show indeed that early entry is not always an optimal strategy to succeed in the technology markets when the pace of technology evolution is rapid or learning effects are important.

THEORY DEVELOPMENT

Inertia and Momentum Revisited

The concepts of inertia and momentum originate from Physics of motion or Kinematics. Isaac Newton was the one who first formulated these phenomena. Newton's first law of motion states that a body at rest remains at rest, or, if in motion, remains in motion *at a constant velocity* unless acted on by an external force. This law is also known as the *law of inertia*, i.e. the resistance of an object to a change in its state of motion (Halliday et al., 2010; Newton, 1999). In Physics, the inertia of an object is measured by its mass, the amount of matter it has. On the other hand, (linear) *momentum* is defined as the product of an object's mass multiplied by its velocity; $\boldsymbol{p} = m\,.\,\boldsymbol{v}$.[16] Both the mass of the body and its velocity play a role in forming its momentum. The concept of momentum is a linkage between Newton's first and second laws of motion. The second law, or the *law of dynamics,* simply states that for any alteration of motion a force is needed. More specifically, *force* is defined by the change in momentum through time ($\boldsymbol{F} = \frac{d\boldsymbol{p}}{dt} = \frac{d(mv)}{dt}$); for changing the state of a moving object, an external force equal to the change of the momentum in time is needed (Halliday et al., 2010; Newton, 1999). It is harder to stop an object or to change its direction the higher is its velocity and/or the heavier it is. In a nutshell, inertia as the *quantity of material* only depends on the mass of the body, while both mass and velocity determine the *quantity of motion,* or momentum. The more inertia an object has the harder it is to move it. While in a dynamic situation, momentum is the quantity of motion that a moving object possesses. Clearly, much effort is needed to accelerate or decelerate it, if its momentum (mass and/or velocity) is higher. Hence, we could have a tiny, fast particle with a momentum that is higher than a massive, yet slow body. The amount of motion (or kinetic energy) that the former possesses at each time could be far above the latter, as would be the case of a fired bullet versus a kicked ball.

Applying this Physics' conceptualization of momentum to technology adoption under network effects, we can say that when the literature refers to the "self-sustaining market momentum" ignited by the critical mass of users, they only consider the inertial component of momentum, which is the mass, and overlook the dynamic component, i.e. velocity. Accordingly, almost all studies operationalize momentum by the size of installed

[16] As velocity and hence momentum are vectors (have both the magnitude and direction) they are written in bold characters.

user base, either implicitly or explicitly. As mentioned earlier, though Katz and Shapiro (1992) formulated the conditions for the excess inertia situation, they also pictured the possibility of an opposite situation called insufficient friction. However, this aspect has not received much attention in the literature, conceptually and empirically, with few notable exceptions (e.g., Suarez and Lanzolla, 2007; Zhu and Iansiti, 2012).

We argue that borrowing the more accurate meaning of momentum from Physics and considering both mass and velocity components can illuminate excess inertia and insufficient friction scenarios of technology selection dynamics in a more consistent manner. In particular, it is quite feasible that a technology with small user base overtakes a large incumbent because the *velocity* of the former is far above the latter, and its market momentum succeeds to attract customers. It can also explain the coexistence of multiple incompatible technologies or competing platforms; the lack of comparative mass of customers in one can be compensated by a higher velocity and relatively the same momentum for both technologies which leaves room for their symbiosis. In the following, we clarify the metaphor of velocity in more detail.

Despite the fact that the provision of complementary goods and/or users on a platform technology attracts more customers, in a wide range of industries with network externalities, not only do customers care about the accumulated stock of complements when assessing the value of the platform, but they also care about new complements that have recently been released (Binken and Stremersch, 2009; Zhu and Iansiti, 2012) and/or the type of participation of users that have recently adopted the technology (Suarez, 2005). For instance in the content-sharing platforms, although users are better off having a large pool of content to choose from, they are also particularly interested (if not more) in the newly uploaded videos, photos, ads and so on (Evans and Schmalensee, 2010). This can be seen especially in many media, advertisement and e-commerce portals such as Airbnb, YouTube, eBay, Groupon and the like. Hence, building market momentum for a platform technology would require not only amassing a stock of complements but also renovating this stock with new complements. Accordingly, we disentangle the momentum effect in two components: the inertial effect (or mass), which we conceive of as the *cumulative* network size at each period; the dynamic effect (or velocity), which we conceive of as the *change* in the network size from previous period. We refer to the former as *stock* and the latter as *novelty* effect. Analogous to the momentum concept in Physics, the former is the total number of game titles, while the latter is the velocity of games provision[17]. The relative significance of these effects is a matter of context. In some industries, the novelty effect could be much more important for boosting the market momentum and rising the adoption. In other words, the value of the complements to the customers is not everlasting, yet decays over time. In some sectors such as media/news and entertainment this decay effect if more accentuated, as is in our empirical context, the video game industry. Although gamers care about the library of games available for a console, they are much more interested in newly released games (as we shall argue more in detail below).

[17] One could argue that velocity and mass in the momentum formula are of different physical dimensions (i.e., distance per time vs. mass) or units of measure (e.g., meters per second vs. kilograms), while in our conceptualization both stock and novelty corresponds to the number of complements/games. Clearly in the context of technology adoption, we cannot apply an identical analogy since the platforms do not *move* in a physical distance dimension but *evolve* through time. Hence, the corresponding velocity in this context is conceptualized as the pace of this evolution, i.e. provision of complements per period.

We expect that both the stock (mass) of available complements and the newly released ones (velocity) affect the momentum of a platform. In line with the existing literature, and pertaining to the inertial component of the momentum, the stock (mass) of complements is expected to affect positively the adoption of the platform by users. Also, pertaining to the dynamic component of the momentum, we expect the number of newly released complements (the velocity) to affect momentum, such that the higher the number of newly released complements, the more the user adoption. Formally stated,

H0. The stock of complements previously released on a platform has a positive impact on platform adoption by users.

H1. The more the number of novel complements available for a platform, the more the platform adoption by users.

In our context, we expect that gamers value the new game titles much more than old ones, and thus the effect of velocity (the novelty of games) to be greater than the effect of stock of complements. As is generally the case with entertainment goods, games get played out soon; gamers always look for new titles to satisfy their consumption needs – in other words, game title complements are durable goods with an accelerated decay effect (Binken and Stremersch, 2009; Clements and Ohashi, 2005). This renders available titles released in the past less appealing to users with the passing of time relative to novel titles. Moreover, although a wide stock of complements signals that final users might more likely find a (variety of) product(s) that match their preferences and consumption needs, most recent products are generally those making news and creating more buzz around a technology system, particularly if these products turn very popular.

In fact, it has been found that one newly released high-quality and popular game may on average explain up to 14 percent increase in platform adoption (Binken and Stremersch, 2009). Being what consumers readily observe, novel platform complements would act as the main reference point in the consumers' decisional process about what technology to adopt. We thus expect the velocity component to outweigh the mass component of the overall momentum effect for the adoption of a given console platform.

> *H2. The positive impact of novel complements is stronger relative to the previous stock of complements on platform adoption in the video game industry.*

DATA, METHOD, AND RESULTS

Data

Our original dataset contains 910 monthly observations of game console sales and the number of games published for each console from January 1995 to June 2008. These data along with other information such as introduction date of each console and its average selling price are obtained from NPD group. We aggregate this primary dataset to quarter level. Specifically, all *quarterly* variables are computed as the median of that variable in each quarter. Our final sample consists of 293 platform-quarter observations.

Variables

Dependent variables

We have two sets of dependent variables for platform adoption by users. One is the cumulative number of unit sales of the game console until that period which accounts for the overall platform adoption from its launch. The others address the dynamic and evolutionary nature of platform adoption at each quarter. These variables measure unit sales, market share and market share within generation of the platform at each period. Specifically, the two latter variables account for the platform adoption relative to its rivals, across and within the same console generation.

Independent variables

We build two primary independent variables to estimate the effect of game titles´ *stock* vis-à-vis new titles (*novelty*) on a platform adoption. *Novelty* reflects the number of new titles released for a console from a given quarter(s). In particular, we have four different measures for novelty; number of titles released from last quarter (Q=-1), from last two quarter (Q=-2), from last three quarters (Q=-3), and from last year (Q=-4).The *stock* variable accounts for all titles from the launch of the platform until last year. To check robustness of the results, we build an alternative measure for stock as all titles published on the platform up to the previous quarter(s).

Control variables

We control for the *number of active platform*s in the market to address the competitive dynamics of the market. Moreover, following previous studies we control for the game console's average *price*. Console pricing as a competitive strategy for the platform is an important driver for penetrating the market. Furthermore, it has been established in the literature that platform age has a curvilinear effect on the console adoption by users and on game developers' decision to publish on the platform. More specifically to our study, the trend of new game titles usually decays as the platform approaches the end of its lifecycle. Thus, we control for the *age* of the platform along its squared term. The exact definitions of all variables and pertaining natural logarithm transformations are provided in Table 2. Additionally, we also control for seasonality and platform time-invariant effects by including quarter-of-year and platform dummy variables.

TABLE 2
Variables definition

Variables		***Definition***	***Transformation method***
Cumulative sale	*Dependent variables*	Cumulative unit sales of the console until end of each quarter	Ln(x)
Sale		Unit sales of the console at each quarter	Ln(x)
Market share		unit sales of game consoles divided by all sold consoles of active platforms at each quarter	Ln(x)
Market share within generation		Unit sales of consoles divided by all sold consoles of active platforms in the same technology(console) generation at each quarter	Ln(x)
Novelty: New titles from Qi	*Independent*	Number of new titles published on the platform in last i quarters	Ln(x+1)
Stock: Total titles until Qi		Number of all titles published on the platform until last year (and alternatively, until the beginning of last i quarters)	Ln(x+1)
Price	*Control variable*	Quarterly retail price of the game console in U.S. dollars	Ln(x)
Age		Number of quarters since the launch of the platform	-
Active platforms		Quarterly number of active platforms at each quarter	-
Exchange rate	*Instrumental variables*	Quarterly exchange rates between the U.S. Dollar and the currency of the country where the console is manufactured	-
Average titles age in the market		Quarterly average age of active titles in the market	-
Television household		Quarterly number of television household	Ln(x)

Empirical strategy

We build our estimation model as $Platform\ Adoption_{it} = \Pi_i + \phi_t + \beta\ X_{it} + \boldsymbol{\epsilon_{it}}$ **;** where Π_i is platform fixed effects to control for unobserved and time-invariant heterogeneities across platforms such as differences in technologies or brand perception by customers. ϕ_t , time fixed effects, accounts for seasonal trend in the game industry. X_{it} is the vector of independent and control variables, and $\boldsymbol{\epsilon_{it}}$ is the error term.

Our independent variables and one of our control variables, price of the console, seem to be endogenous to our model. For instance, there could be some unobservable factors of the console in the error term, such as perceived value of the console by consumers and/or its brand image, which correlate with the willingness to pay, thus price of the console and/or the decision of the game developers for publishing on that platform. Hence, we apply a two-stage least squares (2SLS) model to overcome the violation of OLS assumptions due to the correlation of the endogenous variables with the error term.

Following the previous studies in video game industry (Cennamo and Santalo, 2013; Clements and Ohashi, 2005; Corts and Lederman, 2009) we apply the quarterly exchange rates between the U.S. dollar and the currency of the country where the console is manufactured as an instrument for the price. This variable as a determinant of the production cost should affect the retail price of the console in U.S. but, as an industry aggregate factor, is uncorrelated with the unobserved attributes of each platform, which constitute the error term in our model.

We instrument the number of titles published on the platform, generally, by two instrumental variables. First, the average age of active titles in the market. This variable is a signal for remaining life cycle of the game titles in the market and can alter the game developers' decision about publishing (new) game in the market. Yet, as a market aggregate variable, it is independent of the error term in platform-level adoption model. Second, (the natural logarithm of) the number of television households; this variable as a measure of potential buyers of the video game systems has an impact on developers to enter into the game industry market and publish games but again uncorrelated with individual platform adoption. Particularly, we instrument novelty variable with the former, and stock variable with the latter[18].Both of these variables are used in previous studies on video game as instruments (Cennamo and Santalo, 2013; Clements and Ohashi, 2005; Corts and Lederman, 2009).

As aforementioned, instruments do not change across platforms. Thus, we also interact each of these instruments with dummies for each platform as additional instrumental variables to account for cross-sectional variation (i.e., differences in how platform game titles and price varied to changes in the aging of current titles, size of potential household market, and U.S. dollars' exchange rate).

We use clustered (by platform) robust standard error models in all our analyses to control for the plausible correlation of error terms of the observations that belong to the same platform and for arbitrary heteroskedasticity. On the other hand, we have many excluded instruments in the first stage of our 2SLS models (as for the interaction terms with platform dummies) which are much more than the number of clusters. In this circumstances, the covariance matrix of orthogonality conditions is not of full rank, and over-identification tests are infeasible. Table 3 depicts the results of all first stages when novelty is defined as the number of titles released from last quarter, and stock as all titles until last year. As it shows, they are consistent with the expectations, and the impacts of instrumental variables on the corresponding endogenous variables are significant. For instance, the number of television household until last year affects positively ($\beta=0.151$, $p < 0.001$) the total games title until then; the higher the potential demand for video game system, the more willing are the game developers to publish. The impact of the change

[18] The instrumental variables are constructed identically to the time series operators (lag and difference) used for generating novelty and stock variables from all titles.

in average age of the titles in the market on pace of new titles published on a platform is not clear theoretically: higher average age may indicate the obsolescence of game titles and at the same time the presence of long-lived "blockbuster" games (Cennamo and Santalo, 2013: 1337). We find a significant negative effect (β=0.517, $p < 0.01$) on new titles released from the last quarter. The impact of the exchange rate on price is also positive and significant (β=256.106, $p < 0.001$).

Moreover, investigating various weak instrument identification tests supports the validity and relevance of our instrumental variables. Following Staiger and Stock (1997), as we have F-statistics above 10 there would be no concern about weak instruments: weak correlation of the instrument with the endogenous regressors. Additionally, Angrist and Pischke test, as a more recent one (Angrist and Pischke, 2008), rejects the null hypothesis of weak and under-identification for each of our instruments. Finally, the joint significance of our instruments is confirmed by Anderson-Rubin Wald test. Here, rejecting the null hypothesis means that our instruments are relevant: they are, in fact, correlated with the endogenous regressors (Stock and Yogo, 2005; Wooldridge, 2002). The output of all above tests are reported in Table 3.

TABLE 3
First stage of 2SLS regression and post estimation tests

Variables	*Ln(New titles from Q=-1)*	*Ln(Total titles until Q=-4)*	*Ln(Price)*
Ln(Television household until Q=-4)	-.050*	0. .151***	-.040***
	(0. 022)	(0. .017)	(0.008)
Average titles age in the market (from Q=-1)	-0.517**	-0.751***	-0.063
	(0. 116)	(0.105)	(0.042)
Exchange rate	462.758***	252.547***	256.106***
	(76.994)	(45.668)	(29.951)
Age	-.050+	0.128***	-0.054***
	(0. .027)	(0. .014)	(0.011)
Age^2	-.001**	-0.003***	0.000
	(0. .000)	(0.000)	(0.000)
Active platforms	-.053	0. 175	-0.106
	(0. 167)	(0. 178)	(0.067)
Platform fixed effects	YES	YES	YES
Platform fixed effects × Ln(Television household until Q=-4)	YES	YES	YES
Platform fixed effects × Average titles age in the market from Q=-1	YES	YES	YES
Platform fixed effects × Ln(Exchange rate)	YES	YES	YES
Seasonal fixed effects	YES	YES	YES
Constant	-1.604*	1.327*	3.221***
	(0. .638)	(0. .591)	(0. 257)
Observations	293	293	293
R^2	0.90	0.95	0.93
Instrumented Variable	F test of excluded instruments	Angrist-Pischke under-indented instrument test	Angrist-Pischke weak instruments test
Ln(New titles from Q=-1)	F(42,13)=66.55 p=0.000	F(40,13)= 9.9e+09 p=0.000	F(40,13)= 1.8e+08 p=0.000
Ln(Total titles until Q=-4)	F(42,13)= 27.25 p=0.000	F(40,13)= 178.59 p=0.000	F(40,13)= 3.28 p=0.012
Ln(Price)	F(42,13)= 290.05 p=0.000	F(40,13)= 9847.41 p=0.000	F(40,13)= 180.85 p=0.000
Anderson-Rubin Wald test	F(6,13)= 2174.26 p=0.000	Chi-square(6)= 17759.02 p=0.000	

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All models are the first stages of 2SLS regressions with clustered (by platform) robust standard errors.

Descriptive statistics

Table 4 shows the descriptive statistics of all variables.

TABLE 4
Descriptive statistics

Variables	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Ln(Cumulative sale)	293	15.135	1.888	8.761	17.547
Ln(Sale)	293	11.169	3.104	0.693	15.317
Ln(Market share)	293	-3.451	3.070	-13.732	-0.377
Ln(Market share within generation)	293	-2.044	2.791	-13.641	0
Ln(All titles)	293	5.677	1.258	0.693	7.449
Ln(New titles from Q=-1)	293	2.127	1.609	0	4.700
Ln(New titles from Q=-2)	293	2.733	1.820	0	6.507
Ln(New titles from Q=-3)	293	3.116	1.912	0	6.534
Ln(New titles from Q=-4)	293	3.406	1.943	0	6.572
Ln(Total titles until Q=-1)	293	5.477	1.610	0	7.438
Ln(Total titles until Q=-2)	293	5.200	1.975	0	7.415
Ln(Total titles until Q=-3)	293	4.926	2.249	0	7.377
Ln(Total titles until Q=-4)	293	4.659	2.463	0	7.344
Ln(Price)	293	4.696	0.774	2.754	6.394
Age	293	18.447	12.807	1	52
Active platforms	293	2.812	1.118	1	5
Exchange rate	293	0.009	0.001	0.007	0.012
Average titles age	293	15.135	1.888	8.761	17.547
Ln(Television households)	293	11.169	3.104	0.693	15.317

One of the important concerns in our models is the potentially high correlation between new titles (novelty) and all previous titles (stock). However, as Panel A in Table 5 depicts, the correlations between the two sets of variables do not show any evidence of severe multicollinearity issue. We also detrend the previous titles variables to free them up from a linear cumulative trend in Table 5, Panel B. The results are qualitatively the same.

TABLE 5

Panel A- Correlation matrix for novelty and stock variables

Variables		**1**	**2**	**3**	**4**	**5**	**6**	**7**
1.Ln(New titles from Q=-1)	*Novelty*	1						
2.Ln(New titles from Q=-2)		0.912*						
3.Ln(New titles from Q=-3)		0.886*	0.969*					
4.Ln(New titles from Q=-4)		0.865*	0.946*	0.980*				
5.Ln(Total titles until Q=-1)	*Stock*	-0.134*	-0.079	-0.034	0.008			
6.Ln(Total titles until Q=-2)		-0.129*	-0.185*	-0.124*	-0.073	0.918*		
7.Ln(Total titles until Q=-3)		-0.178*	-0.216*	-0.204*	-0.145*	0.869*	0.935*	
8.Ln(Total titles until Q=-4)		-0.237*	-0.261*	-0.241*	-0.215*	0.835*	0.885*	0.945*

All correlations with asterisk are significant at the .05 level.

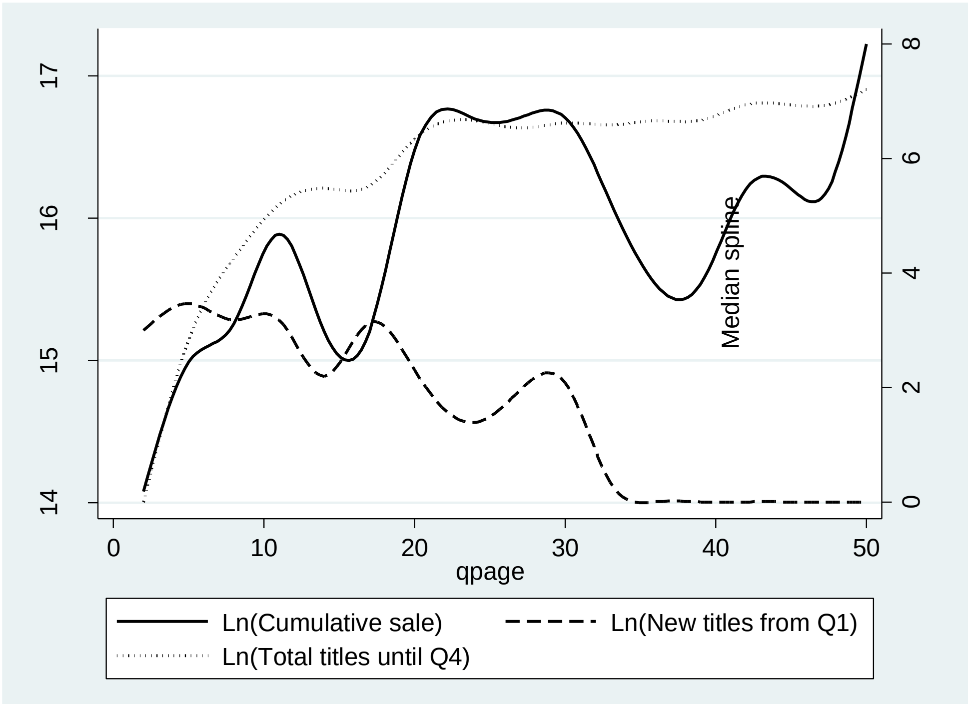
Panel B- Correlation matrix for novelty and (detrended) stock variables

Variables		**1**	**2**	**3**	**4**	**5**	**6**	**7**
1.Ln(New titles from Q=-1)	*Novelty*	1						
2.Ln(New titles from Q=-2)		0.912*						
3.Ln(New titles from Q=-3)		0.886*	0.969*					
4.Ln(New titles from Q=-4)		0.865*	0.946*	0.980*				
5.Ln(Total titles until Q=-1)	*Stock*	-0.176*	-0.102*	-0.049	-0.001			
6.Ln(Total titles until Q=-2)		-0.172*	-0.212*	-0.142*	-0.084	0.913*		
7.Ln(Total titles until Q=-3)		-0.225*	-0.245*	-0.225*	-0.159*	0.861*	0.930*	
8.Ln(Total titles until Q=-4)		-0.288*	-0.294*	-0.266*	-0.232*	0.824*	0.877*	0.941*

All correlations with asterisk are significant at the .05 level.

Figure 1 illustrates the median time series (median-spline plots) of dependent and independent variables for platforms altogether. In line with our expectations, especially once the dynamics of competition is taken into account (as shown in unit sale graph, Panel B, and similar to market share measures, not reported here, but available upon request), the fluctuation of platform adoption is much more analogous to the number of recently published titles' pattern (i.e., novelty) rather than total number of titles that are released previously (i.e., stock). To be sure that the stronger one-by-one correspondence between new titles and platform adoption is not merely because of the cumulative essence of accumulated number of previous titles, we plot the graphs after detrending the latter one to see its variation more clearly. Above interpretation still holds in Figure 2.

FIGURE 1
Median time series of new and total title variables vs. sales and cumulative sales
Panel A



Panel B

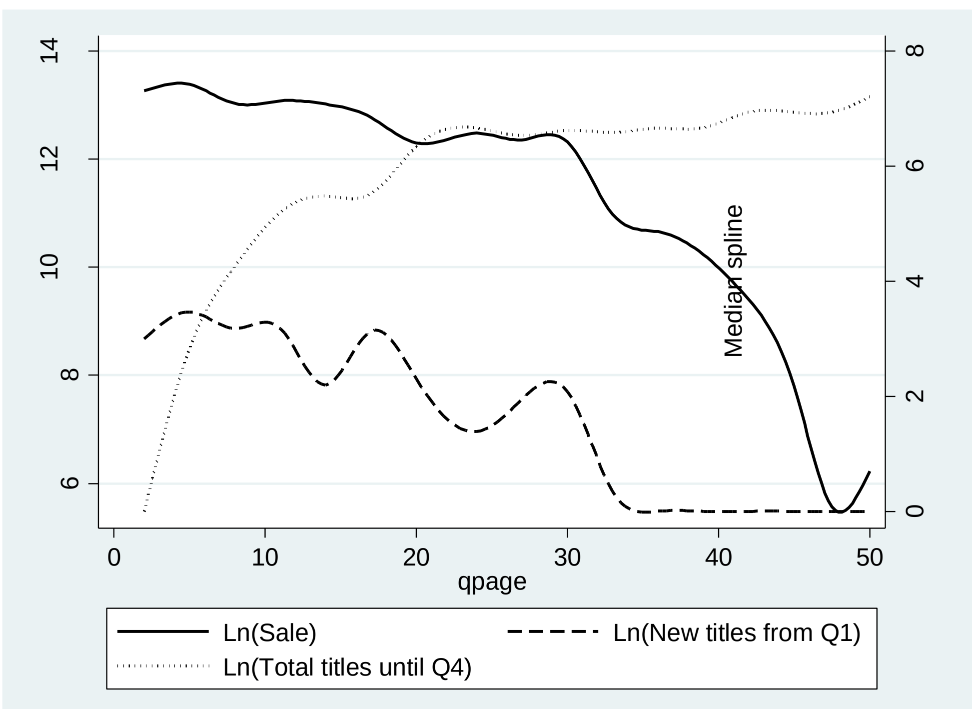
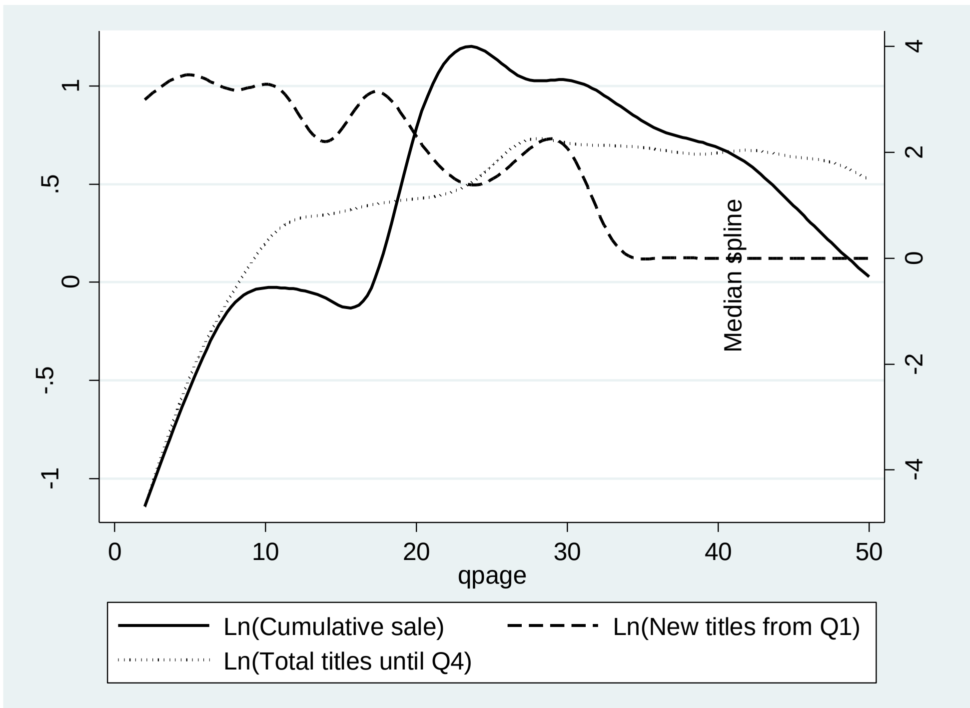
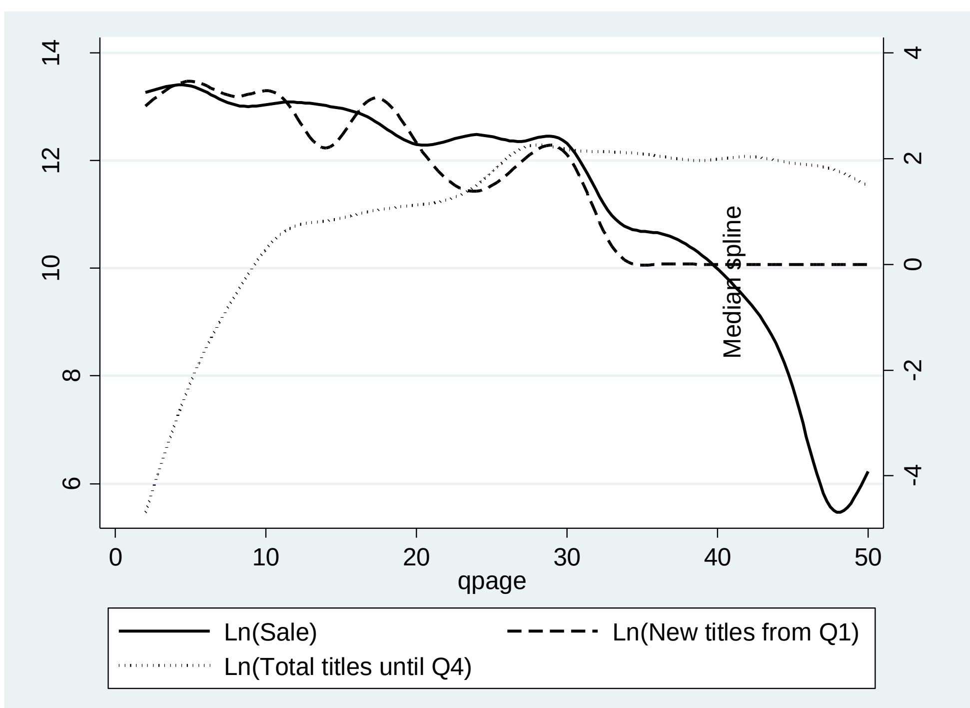


FIGURE 2
Median time series of new and (detrended) total title variables vs. sales and (detrended) cumulative sales

Panel A



Panel B



Results

Table 6—the second stage result of the 2SLS model with clustered robust standard errors at platform level—displays the first to fourth quarter models estimate the distinct effect of *novelty*, the number of new titles released since the last Q (Q=-1, -2,-3,-4) quarter(s), and of *stock*, the total number of titles released until last year, on platform adoption. Accordingly, both new titles and the stock of titles positively affect the platform cumulative sales in all models. For instance in model Q=-2, the effect of stock of titles in last year ($\beta=0.240$, $p < 0.001$) and new titles released in last two quarters ($\beta=0.157$, $p < 0.001$) significantly increase the cumulative sale of the game console. The former supports Hypothesis 0, while the latter corroborates Hypothesis 1. However, the effect of stock is stronger in all specification but Q=-1. In this case, 100 new titles in the current quarter would increase platform cumulative sales by 25 percent, while a similar expansion of the stock of titles in the previous year would account for 20 percent cumulative sales' increase. Yet, when we consider more than the current quarter when accounting for novelty, the effect is reversed. For instance, in the "two quarters" model (Q=-2), 100 more titles in the library of the platform until last year would lead to 24 percent higher cumulative sales ($\beta=0.240$, $p < 0.001$), while the same amount of new titles released in the last two quarters results in roughly 16 percent increase in the overall adoption ($\beta=0.157$, $p < 0.001$). However, applying a t-test reveals that in none of these models the coefficients for novelty and stock variables are statistically different from each other (p-value>0.1), as is reported in Table 6. So the interpretation pertaining to the second hypothesis, for this dependent variable, should be considered cautiously.

TABLE 6
Ln(Cumulative sale)

Variables	*Q=-1*	*Q=-2*	*Q=-3*	*Q=-4*
Ln(New titles from Q=-1)	0.294***			
	(0.079)			
Ln(Total titles until Q=-1)	0.218**			
	(0.073)			
Ln(New titles from Q=-2)		0.183***		
		(0.054)		
Ln(Total titles until Q=-2)		0.260***		
		(0.033)		
Ln(New titles from Q=-3)			0.161**	
			(0.052)	
Ln(Total titles until Q=-3)			0.255***	
			(0.027)	
Ln(New titles from Q=-4)				0.173***
				(0.047)
Ln(Total titles until Q=-4)				0.240***
				(0.026)
Ln(Price)	-0.396**	-0.249**	-0.227*	-0.184*
	(0.123)	(0.094)	(0.090)	(0.083)
Age	0.074***	0.059***	0.049***	0.048***
	(0.018)	(0.011)	(0.009)	(0.008)
Age^2	-0.001*	-0.000+	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Active platforms	0.103**	0.069+	0.033	0.023
	(0.035)	(0.039)	(0.044)	(0.048)
Platform fixed effects	YES	YES	YES	YES
Seasonal fixed effects	YES	YES	YES	YES
Constant	11.920***	11.112***	11.172***	11.023***
	(0.790)	(0.512)	(0.502)	(0.419)
Observations	293	293	293	293
R^2	0.98	0.98	0.98	0.98
Adjusted R^2	0.97	0.98	0.98	0.98
Novelty vs. Stock effect t-test (null: no difference)	*p= 0.460*	*p= 0.180*	*p= 0.136*	*p= 0.234*

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All models are second stages of 2SLS regressions with clustered (by platform) robust standard errors.

As an alternative measure for stock, instead of the number of titles released until the last year, for a given quarter we construct the stock as all the titles until the beginning of that quarter. The results for this alternative measure of stock, a similar pattern as previous, are provided in Table 7.

TABLE 7
Ln(Cumulative sale)- alternative measure for stock

Variables	***Q=-1***	***Q=-2***	***Q=-3***	***Q=-4***
Ln(New titles from Q=-1)	0.294***			
	(0.079)			
Ln(Total titles until Q=-1)	0.218**			
	(0.073)			
Ln(New titles from Q=-2)		0.183***		
		(0.054)		
Ln(Total titles until Q=-2)		0.260***		
		(0.033)		
Ln(New titles from Q=-3)			0.161**	
			(0.052)	
Ln(Total titles until Q=-3)			0.255***	
			(0.027)	
Ln(New titles from Q=-4)				0.173***
				(0.047)
Ln(Total titles until Q=-4)				0.240***
				(0.026)
Ln(Price)	-0.396**	-0.249**	-0.227*	-0.184*
	(0.123)	(0.094)	(0.090)	(0.083)
Age	0.074***	0.059***	0.049***	0.048***
	(0.018)	(0.011)	(0.009)	(0.008)
Age^2	-0.001*	-0.000+	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Active platforms	0.103**	0.069+	0.033	0.023
	(0.035)	(0.039)	(0.044)	(0.048)
Platform fixed effects	YES	YES	YES	YES
Seasonal fixed effects	YES	YES	YES	YES
Constant	11.920***	11.112***	11.172***	11.023***
	(0.790)	(0.512)	(0.502)	(0.419)
Observations	293	293	293	293
R^2	0.98	0.98	0.98	0.98
Adjusted R^2	0.97	0.98	0.98	0.98
Novelty vs. Stock effect t-test (null: no difference)	*p= 0.575*	*p= 0.242*	*p= 0.124*	*p= 0.234*

Standard errors in parentheses, + p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001
All models are second stages of 2SLS regressions with clustered (by platform) robust standard errors.

Elaborating the findings in Table 6, we replace the cumulative sale with *dynamic* and real-time indicators of the adoption, such as sale at each quarter in Table 8. Both of the new titles and previous titles still significantly have a positive effect on the platform adoption, supporting Hypothesis 0 and 1. Also, corroborating Hypothesis 2 the impact of new titles is much stronger now in all models (Q=-1, -2, -3, -4). For instance the impact of new titles in the last two quarters on sale (β=1.154, $p < 0.001$) is almost 5 times bigger and stronger than the effect of all titles until last year (β=0.276, $p < 0.05$), as reported in Table 8. This pattern is similar in all other measures of adoption (market share, and market share within given generation) in Table 9. As reported in the tables applying a t-test confirms, in all models, the statistical significance for the difference between novelty and stock coefficients.

TABLE 8
Ln(Sale)

Variables	***Q=-1***	***Q=-2***	***Q=-3***	***Q=-4***
Ln(Total titles until Q=-4)	0.172*	0.276**	0.314**	0.301**
	(0.086)	(0.101)	(0.104)	(0.103)
Ln(New titles from Q=-1)	1.271***			
	(0.305)			
Ln(New titles from Q=-2)		1.154***		
		(0.299)		
Ln(New titles from Q=-3)			1.144***	
			(0.296)	
Ln(New titles from Q=-4)				1.139***
				(0.308)
Ln(Price)	0.222	-0.225	-0.424	-0.480
	(0.640)	(0.753)	(0.822)	(0.878)
Age	-0.118	-0.156*	-0.177**	-0.187**
	(0.074)	(0.070)	(0.067)	(0.068)
Age^2	0.001	0.002	0.003*	0.004*
	(0.001)	(0.002)	(0.002)	(0.002)
Active platforms	-0.354*	-0.325+	-0.352	-0.371
	(0.168)	(0.198)	(0.223)	(0.260)
Platform fixed effects	YES	YES	YES	YES
Seasonal fixed effects	YES	YES	YES	YES
Constant	5.781+	5.833+	6.236+	6.288
	(3.150)	(3.355)	(3.629)	(3.876)
Observations	293	293	293	293
R^2	0.83	0.85	0.85	0.85
Adjusted R^2	0.81	0.83	0.83	0.84
Novelty vs. Stock effect	*p= 0.001*	*p= 0.014*	*p=0.020*	*p=0.021*
t-test (null: no difference)				

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All models are second stages of 2SLS regressions with clustered (by platform) robust standard errors.

TABLE 9
Ln(Market share) and Ln(Market share within generation)

	Ln(Market share)				***Ln(Market share within generation)***			
Variables	***Q=-1***	***Q=-2***	***Q=-3***	***Q=-4***	***Q=-1***	***Q=-2***	***Q=-3***	***Q=-4***
Ln(Total titles until Q=-4)	0.140+	0.245*	0.285**	0.275**	0.227***	0.338***	0.361***	0.341***
	(0.083)	(0.097)	(0.102)	(0.101)	(0.068)	(0.085)	(0.092)	(0.094)
Ln(New titles from Q=-1)	1.288***				1.219***			
	(0.310)				(0.282)			
Ln(New titles from Q=-2)		1.167***				1.058***		
		(0.301)				(0.287)		
Ln(New titles from Q=-3)			1.159***				1.052***	
			(0.295)				(0.277)	
Ln(New titles from Q=-4)				1.162***				1.055***
				(0.307)				(0.289)
Ln(Price)	0.530	0.041	-0.190	-0.304	1.276+	0.906	0.664	0.520
	(0.727)	(0.821)	(0.875)	(0.924)	(0.653)	(0.756)	(0.790)	(0.839)
Age	-0.115	-0.157*	-0.180*	-0.194**	-0.040	-0.082	-0.102+	-0.114+
	(0.077)	(0.075)	(0.073)	(0.073)	(0.061)	(0.060)	(0.060)	(0.062)
Age^2	0.000	0.002	0.003+	0.004+	0.007***	0.009***	0.010***	0.011***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Active platforms	-0.422*	-0.401*	-0.433+	-0.462+	-0.707***	-0.694***	-0.721***	-0.747**
	(0.173)	(0.198)	(0.222)	(0.256)	(0.170)	(0.177)	(0.198)	(0.229)
Platform fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Seasonal fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Constant	-9.335**	-9.088*	-8.532*	-8.220*	-11.083***	-11.225***	-10.526**	-10.005**
	(3.523)	(3.585)	(3.783)	(3.994)	(3.128)	(3.259)	(3.404)	(3.640)
Observations	293	293	293	293	293	293	293	293
R^2	0.83	0.85	0.85	0.85	0.83	0.85	0.85	0.85
Adjusted R^2	0.81	0.83	0.83	0.83	0.82	0.84	0.84	0.84
Novelty vs. Stock effect t-test (null: no difference)	*p= 0.000*	*p= 0.006*	*p= 0.008*	*p= 0.010*	*p= 0.000*	*p= 0.024*	*p= 0.027*	*p= 0.029*

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All models are second stages of 2SLS regressions with clustered (by platform) robust standard errors.

Robustness tests

One can argue that our results are likely to suffer from an endogeneity problem. In particular, there could be some (unobserved) variables, such as price promotion, advertisement, and marketing campaign, that affect the platform adoption and could be highly correlated with the new titles released, yet have a weak, if any, correlation with previous titles. That is, the strong coefficient found for novelty, compared to stock, could be driven by these omitted variables. In other words, although we have already controlled for the time-invariant attributes *across platforms* such as brand image, by including platform dummies in the models, there could be *within-platform* factors that vary across time, hence bias our differential impacts of recent versus previous titles released on a given platform. Addressing this concern we take steps to verify the trustworthiness of our findings. First, as illustrated in previously reported results, altering the time frame for novelty definition (i.e. titles released in recent last one, two, three, or four quarters) does not change the findings. Moreover, as mentioned later, running the same models at month level with different time frames results in a qualitatively similar pattern. Although the concern still remains, similar findings for various specifications for recent/previous period to define novelty/stock diminishes the concern about time-dependent bias to some extent. Second, we have already interacted the platform dummies with instrumental variables for stock, novelty, and price variables in the first stage of the 2SLS models to account for time-variant heterogeneity of platforms pertaining to above instrumented variables.

Third, we replace our dependent variable at time *t* by its lead version at time *t+1*. Panel A in Table 10 displays the results for unit sale of the game console as dependent variable, which are perfectly supportive as before. The results for other measures of the dependent variable are also supportive, not reported here but available upon request. Here, the unobserved attributes of the platform at time *t+1* have a weak, if any, correlation with both novelty and stock at previous periods. One can still argue that new games are still *closer* to the dependent variable than the old ones, which means higher correlation and still an upward bias for novelty variable. Nevertheless, in this new specification, at least the potential inflation of novelty coefficient is lessened. Especially, when we lead the dependent variable even to one year (four quarters) ahead, at *t+4*, to be *far* enough from both novelty at time *t* and stock variables, as Panel B in Table 10 shows, the results are the same.

TABLE 10
Ln(Sale)-Lead version

	Panel A				**Panel B**			
	$Ln(Sale)_{t+1}$				**$Ln(Sale)_{t+4}$**			
Variables	***Q=-1***	***Q=-2***	***Q=-3***	***Q=-4***	***Q=-1***	***Q=-2***	***Q=-3***	***Q=-4***
Ln(Total titles until Q=-4)	0.150+	0.311**	0.365**	0.353**	0.129	0.291*	0.372***	0.396***
	(0.085)	(0.111)	(0.116)	(0.116)	(0.091)	(0.118)	(0.093)	(0.073)
Ln(New titles from Q=-1)	1.417***				1.476***			
	(0.278)				(0.278)			
Ln(New titles from Q=-2)		1.209***				1.261***		
		(0.278)				(0.290)		
Ln(New titles from Q=-3)			1.198***				1.123***	
			(0.274)				(0.310)	
Ln(New titles from Q=-4)				1.174***				1.087**
				(0.287)				(0.337)
Ln(Price)	-0.132	-0.485	-0.673	-0.666	-0.080	-0.479	-0.311	-0.143
	(0.692)	(0.806)	(0.839)	(0.851)	(0.657)	(0.889)	(1.053)	(1.169)
Age	-0.141*	-0.196**	-0.223**	-0.233**	-0.176*	-0.238**	-0.270**	-0.284**
	(0.072)	(0.073)	(0.074)	(0.075)	(0.080)	(0.080)	(0.084)	(0.090)
Age^2	0.001	0.003*	0.005**	0.006**	0.004*	0.006**	0.007**	0.008**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Active platforms	-0.449+	-0.457	-0.503	-0.527	-0.434	-0.473	-0.556	-0.611+
	(0.233)	(0.279)	(0.311)	(0.347)	(0.270)	(0.319)	(0.339)	(0.361)
Platform fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Seasonal fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Constant	7.264*	6.682+	6.989+	6.725+	5.609	5.025	3.748	2.588
	(3.652)	(3.825)	(3.900)	(3.909)	(3.648)	(4.195)	(4.812)	(5.260)
Observations	279	279	279	279	237	237	237	237
R^2	0.83	0.85	0.85	0.85	0.82	0.83	0.83	0.83
Adjusted R^2	0.82	0.83	0.83	0.84	0.81	0.82	0.81	0.82

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All models are second stages of 2SLS regressions with clustered (by platform) robust standard errors.

Fourth, similar to the remedy proposed by Clments and Ohashi (2005), we introduce year-dummy variables and their interaction with platform fixed effects. Doing so, we account for unobserved attributes of each platform in each year, i.e. within-platform heterogeneity across time. Although we lose significance in some models, the findings follow the same pattern as before. Table 11 illustrates the results for unit sale as dependent variable. As it depicts the coefficient of novelty in last two and three quarters (Q=-2, -3) is positive and significant (β=0.493, $p < 0.01$; β=0.406, $p < 0.05$) and stronger than positive impact of stock (β=0.190, $p < 0.01$; β=0.274, $p < 0.001$).

TABLE 11
Ln(Sale)- Including platform-year fixed effects

Variables	***Q=-1***	***Q=-2***	***Q=-3***	***Q=-4***
Ln(Total titles until Q=-4)	0.235*	0.190**	0.274***	0.145*
	(0.109)	(0.070)	(0.062)	(0.065)
Ln(New titles from Q=-1)	0.236			
	(0.252)			
Ln(New titles from Q=-2)		0.493**		
		(0.156)		
Ln(New titles from Q=-3)			0.406*	
			(0.185)	
Ln(New titles from Q=-4)				0.313
				(0.274)
Ln(Price)	0.726	0.981	0.540	2.533**
	(1.243)	(1.434)	(1.038)	(0.924)
Age	0.029	0.156	0.106	0.283*
	(0.142)	(0.153)	(0.134)	(0.115)
Age^2	0.001	0.001	0.000	-0.002
	(0.002)	(0.002)	(0.002)	(0.003)
Active platforms	-0.070	-0.018	-0.046	0.093
	(0.213)	(0.141)	(0.148)	(0.153)
Platform fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Platform fixed effects × Year fixed effects	YES	YES	YES	YES
Seasonal fixed effects	YES	YES	YES	YES
Constant	5.307	3.747	5.928	-3.678
	(6.096)	(6.912)	(5.349)	(4.541)
Observations	293	293	293	293
R^2	0.96	0.96	0.96	0.95
Adjusted R^2	0.94	0.95	0.95	0.93

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All models are second stages of 2SLS regressions with clustered (by platform) robust standard errors.

Fifth, Following Cort and Lederman (2009), instead of controlling for age of a platform (as a continuous variable) and platform fixed effect separately, we account for both together by defining platform-age (in year) dummy variables. We replace continuous variables for platform´s age and squared age, and platform dummy variables, by these new fixed effects. Again, we control for (unobserved) specific attributes of each platform in each year of its lifecycle. Although unexpectedly the statistical significance of stock variable in most of the models disappears (p-value>0.1), we still have supportive results for the impact of novelty on platform adoption, of which coefficient was suspected to be upward biased. Table 12 displays the results for unit sale as dependent variable. Although comparing to the results in Table 8 the coefficients of novelty variables are deflated, they are still significantly positive and stronger than of stock in all models.

TABLE 12
Ln(Sale)- Including platform-age fixed effect

Variables	***Q=-1***	***Q=-2***	***Q=-3***	***Q=-4***
Ln(Total titles until Q=-4)	0.156	0.115	-0.010	0.200
	(0.150)	(0.091)	(0.042)	(0.129)
Ln(New titles from Q=-1)	1.189***			
	(0.334)			
Ln(New titles from Q=-2)		0.921***		
		(0.212)		
Ln(New titles from Q=-3)			1.053***	
			(0.155)	
Ln(New titles from Q=-4)				1.204***
				(0.155)
Ln(Price)	1.259	1.424***	0.357	0.599
	(0.811)	(0.413)	(0.371)	(0.448)
Active platforms	-0.212	-0.281*	-0.029	0.093
	(0.275)	(0.123)	(0.131)	(0.189)
Platform-age fixed effects	YES	YES	YES	YES
Seasonal fixed effects	YES	YES	YES	YES
Constant	2.370	0.294	3.809*	1.344
	(3.606)	(1.396)	(1.636)	(1.428)
Observations	293	293	293	293
R^2	0.85	0.94	0.96	0.94
Adjusted R^2	0.81	0.92	0.95	0.92

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All models are second stages of 2SLS regressions with clustered (by platform) robust standard errors.

As the last remedy, we include the lagged version of dependent variable at previous quarter in the model, to absorb the omitted variable bias. Accounting for the autocorrelation between lagged and current version of the dependent variable we applied a generalized method of moments (GMM). Specifically, we instrument lagged dependent variable, stock, novelty, and price in a “difference GMM” approach (Arellano and Bond, 1991; Roodman, 2009). This approach first transforms all regressors, by differencing, to build the first difference equation. This transformation, by expunging the fixed effects, eliminates any source of omitted variables. Next, because the first-differenced endogenous variables are still potentially correlated with the error term, applying a GMM estimator, they are instrumented with all their available lags in levels. As the most conservative approach, to also deal with the potential concerns about convenience of our instrumental variables for price, novelty, and stock, we exclude all those “external” instrumental variable, described in the empirical strategy earlier, from GMM specifications and assume that only available instruments are “internal” (Roodman, 2009: 100). In particular, all available lagged versions of price, novelty, and stock, and our dependent variable (as its lag is an additional regressor here) are used as instruments for the first differenced endogenous regressors. All other control variables, excluding price, are assumed to be strictly exogenous, so these regressors themselves are used as their own instruments[19]. Table 13 displays the results for unit sale as the dependent variable. As it depicts, the results corroborate our previously reported findings.

[19] We apply xtabond2 command in Stata to implement the difference GMM style approach, following Roodman (2009).

TABLE 13
Ln(Sale)- General Method of Moments

Variables	***Q=-1***	***Q=-2***	***Q=-3***	***Q=-4***
L.Ln(Sale)	0.712***	0.696***	0.736***	0.730***
	(0.036)	(0.043)	(0.035)	(0.030)
Ln(Total titles until Q4)	0.086*	0.075*	0.122**	0.142***
	(0.035)	(0.036)	(0.038)	(0.036)
Ln(New titles from Q1)	0.649***			
	(0.100)			
Ln(New titles from Q2)		0.474***		
		(0.119)		
Ln(New titles from Q3)			0.311**	
			(0.101)	
Ln(New titles from Q4)				0.335***
				(0.087)
Ln(Price)	-0.087	-0.117	-0.090	-0.170
	(0.189)	(0.217)	(0.217)	(0.216)
Age	-0.040*	-0.056*	-0.076**	-0.086***
	(0.019)	(0.022)	(0.025)	(0.025)
Age^2	0.001***	0.001**	0.002**	0.002***
	(0.000)	(0.000)	(0.001)	(0.001)
Active platforms	-0.091	-0.130	-0.164	-0.177
	(0.077)	(0.097)	(0.120)	(0.131)
Platform fixed effects	YES	YES	YES	YES
Seasonal fixed effects	YES	YES	YES	YES
Observations	265	265	265	265

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All models are second stages of a difference GMM method, with robust standard errors.

Since we have 52 time periods (quarters) for 14 individuals (platforms) in our panel data, using all lagged versions of the variables as instruments generates a large instrument collection which can overfit the endogenous variables, and raise the problem of too-many-instruments in GMM (Roodman, 2009). The available option to deal with this problem is limiting the lag range for constructing the instruments collection. We implement this remedy for different lag limit versions, with similar results. Table 14 shows the results while constraining GMM to use only the second lag of endogenous variables, second to third, and second to fourth lags for building the instrument set. Panel A, B, and C in Table 14 illustrate the pertaining results which are supportive to previous ones. All models in

Tables 10, 11, 12, 13 and 14 are implemented using other measures of platform adoption and the results, not reported here, are qualitatively the same.

TABLE 14
Ln(Sale)- General Method of Moments, limited lag range

	Panel A				*Panel B*				*Panel C*			
Variables	***Q=-1***	***Q=-2***	***Q=-3***	***Q=-4***	***Q=-1***	***Q=-2***	***Q=-3***	***Q=-4***	***Q=-1***	***Q=-2***	***Q=-3***	***Q=-4***
L.Ln(Sale)	0.626***	0.606***	0.639***	0.630***	0.712***	0.696***	0.736***	0.730***	0.712***	0.696***	0.736***	0.730***
	(0.027)	(0.047)	(0.050)	(0.051)	(0.036)	(0.043)	(0.035)	(0.030)	(0.036)	(0.043)	(0.035)	(0.030)
Ln(Total titles until Q4)	0.106*	0.121*	0.178**	0.196***	0.086*	0.075*	0.122**	0.142***	0.086*	0.075*	0.122**	0.142***
	(0.050)	(0.056)	(0.064)	(0.058)	(0.035)	(0.036)	(0.038)	(0.036)	(0.035)	(0.036)	(0.038)	(0.036)
Ln(New titles from Q1)	0.769***				0.649***				0.649***			
	(0.124)				(0.100)				(0.100)			
Ln(New titles from Q2)		0.469**				0.474***				0.474***		
		(0.145)				(0.119)				(0.119)		
Ln(New titles from Q3)			0.269*				0.311**				0.311**	
			(0.115)				(0.101)				(0.101)	
Ln(New titles from Q4)				0.329***				0.335***				0.335***
				(0.078)				(0.087)				(0.087)
Ln(Price)	-0.211	-0.244	-0.245	-0.354	-0.087	-0.117	-0.090	-0.170	-0.087	-0.117	-0.090	-0.170
	(0.212)	(0.336)	(0.359)	(0.360)	(0.189)	(0.217)	(0.217)	(0.216)	(0.189)	(0.217)	(0.217)	(0.216)
Age	-0.057+	-0.094*	-0.126**	-0.132**	-0.040*	-0.056*	-0.076**	-0.086***	-0.040*	-0.056*	-0.076**	-0.086***
	(0.030)	(0.039)	(0.047)	(0.047)	(0.019)	(0.022)	(0.025)	(0.025)	(0.019)	(0.022)	(0.025)	(0.025)
Age^2	0.001	0.001	0.001	0.002*	0.001***	0.001**	0.002**	0.002***	0.001***	0.001**	0.002**	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Active platforms	0.047	-0.066	-0.129	-0.148	-0.091	-0.130	-0.164	-0.177	-0.091	-0.130	-0.164	-0.177
	(0.106)	(0.108)	(0.130)	(0.139)	(0.077)	(0.097)	(0.120)	(0.131)	(0.077)	(0.097)	(0.120)	(0.131)
Platform fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Seasonal fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	265	265	265	265	265	265	265	265	265	265	265	265

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All models are second stages of a difference GMM method, with robust standard errors.

As the final set of robustness tests, we replicate models in Table 7 with the alternative measure for the stock variable, by applying unit sales, market share and market share within generation as dependent variables as well. We also run all analyses in Tables 6, 7, 8 and 9 at month level. The results corroborate the reported findings. The last robustness check results are not reported here, but available upon request.

EXTENSION

The novelty construct advanced here (i.e., the velocity component of momentum) brings about the dynamic and temporal aspect along with the inertia associated with network effects. One shall be able then to assess the evolutionary dynamics at the aggregate industry or technological generation level by looking at the mass and velocity of all of the competing technologies racing *for* the market. As an extension to our study, we try to estimate the *market tipping point* for each generation—the point at which the mass of users in the market will adopt the next-generation technology. As depicted earlier, both the temporal development of complements (novelty) and their accumulated number (stock) matters to drive the momentum of a platform and/or technology.

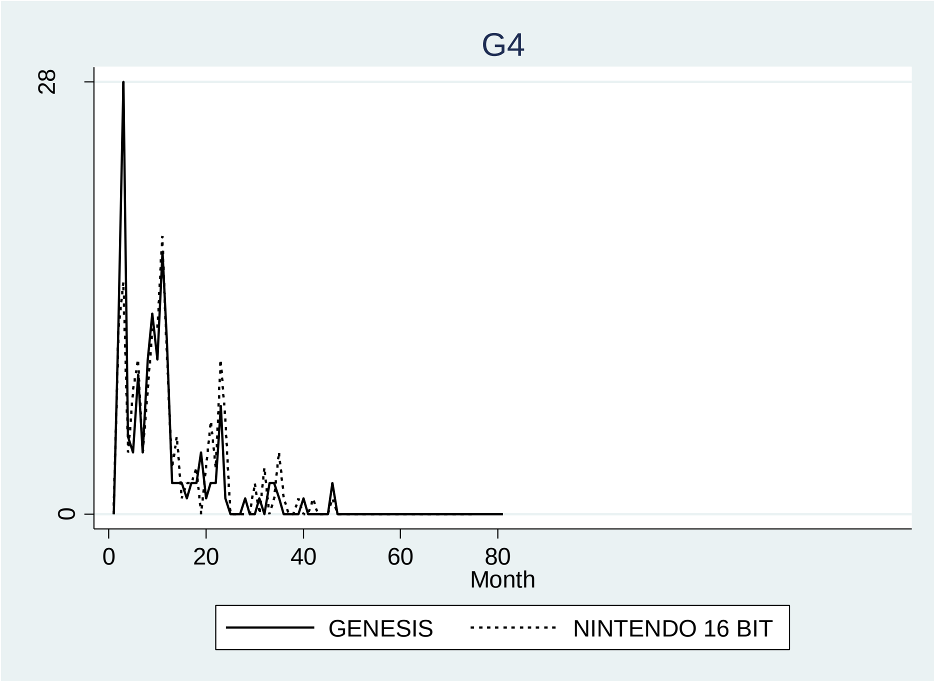
Accounting for the dynamic (temporal) aspect of the momentum, we define the "*agglomeration point"* for platform *p* as $\frac{\sum_{i=1}^{n} t_i \,.m_i}{\sum_{i=1}^{n} \sum mi}$, where m_i stands for the number of games released on platform *p*, at period (month) *i*. This is simply an indicator for a point in time axis around which most of the platform´s activities (game titles provision) are centered[20]. For example as Figure 3 illustrates, PlayStation in generation 5 launched in month 9 of our panel and kept providing game titles until month 121 after which no titles is published on the platform. As the graph shows, most of the games are published in the middle of PlayStation life cycle. Accordingly, in Figure 4, the agglomeration point for this platform is at period 56 which is quite in the middle of its life cycle as expected. In other words, this is the point at which the provision of the (new) games is concentrated

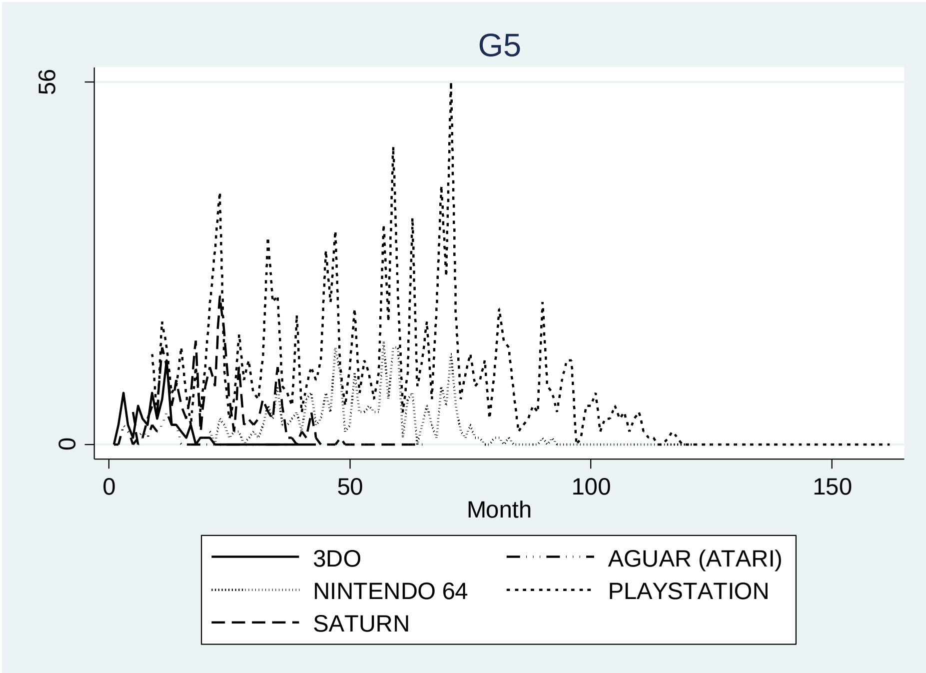
[20] Having a more timely and accurate point estimate, we use the data at month, instead of quarter, level.

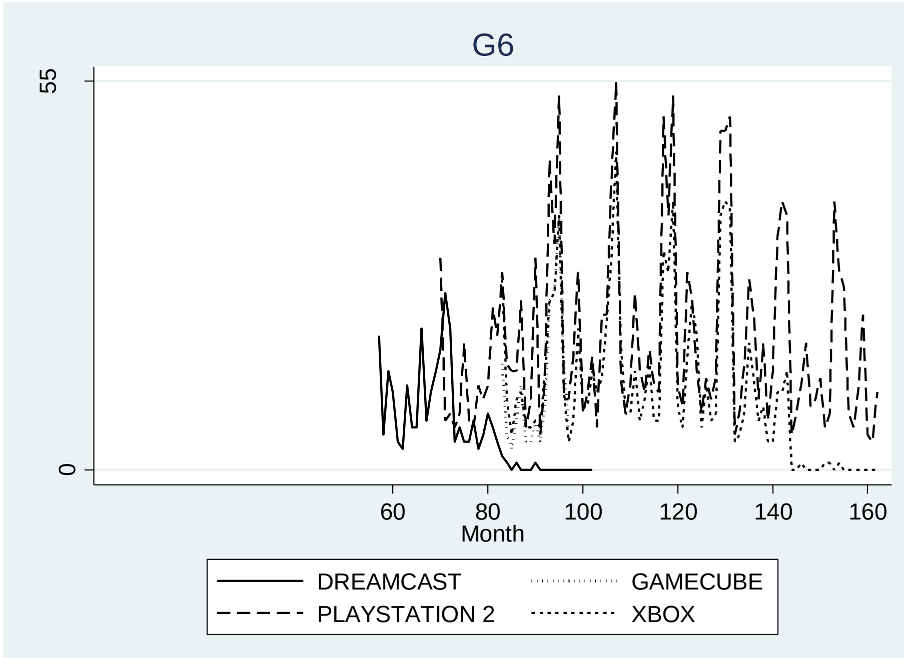
or the platform´s momentum picks. The vertical axis of Figure 4 corresponds to the total number of game titles published on the platform during the lifecycle, and the number beside each platform is the average market share of the platforms within corresponding generation. For instance, PlayStation by average accounts for around 78 percent of all console sales in generation 4 over time.

FIGURE 3

Number of game titles released at each month on platform per generation 4, 5, 6, and 7






G6
55
0
60
80
100
120
140
160
Month
DREAMCAST
GAMECUBE
PLAYSTATION 2
XBOX

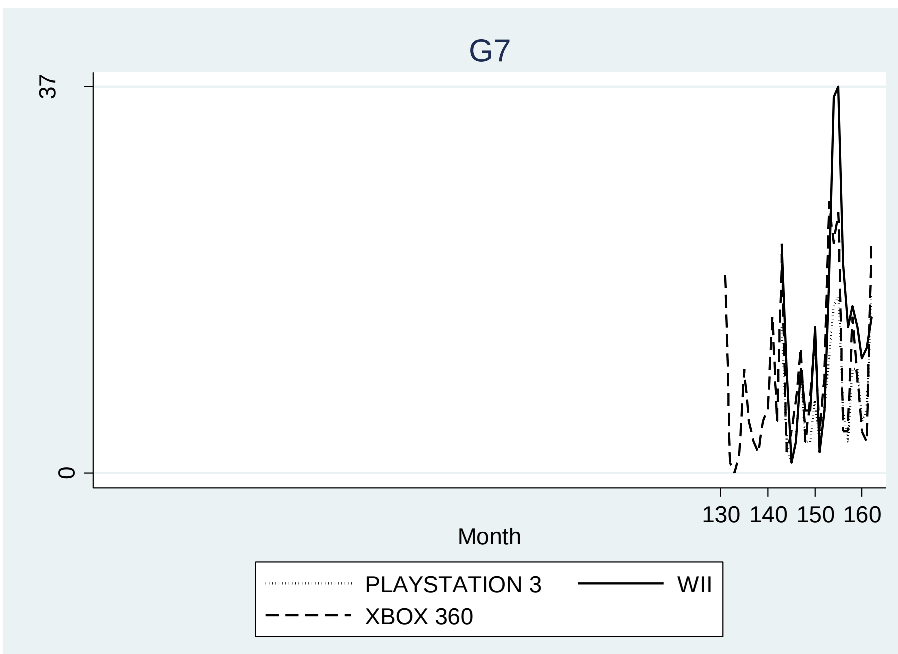
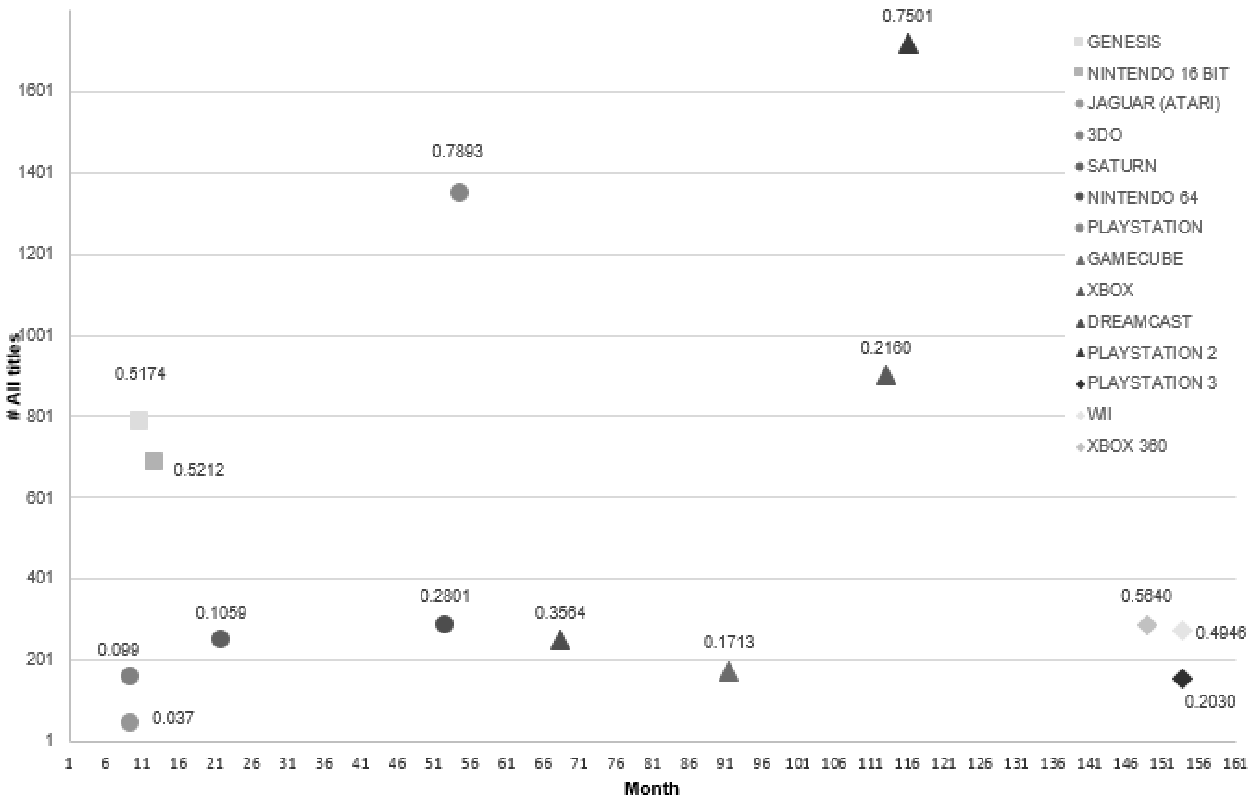

G7
37
0
130
140
150
160
Month
PLAYSTATION 3
WII
XBOX 360

FIGURE 4
Agglomeration point for each platform with corresponding average market share within generation



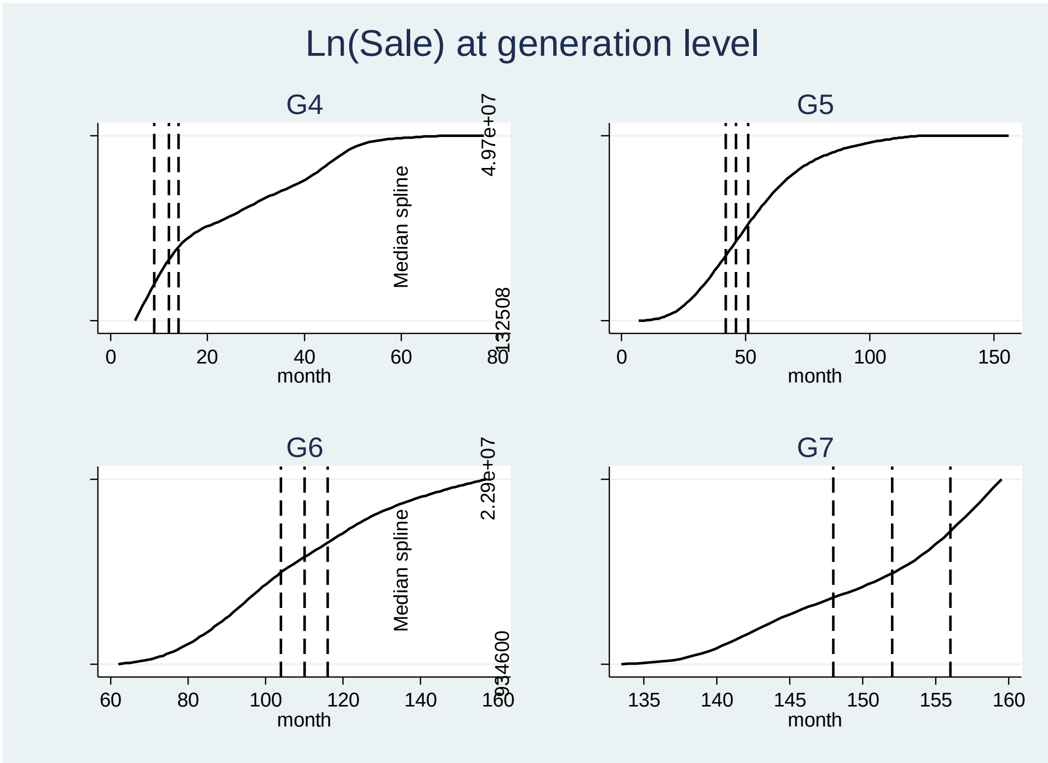
Estimating the market tipping point for each generation, we turn our attention at the aggregate market level. Hence, we should expect that the market for a given generation of competing technologies will start tipping at the point where the momentums (temporal provision of new games) of platforms in that generation peak altogether—the average of agglomeration points of the platforms in that generation. Put differently, it is the point that most of the (new) game titles are provided at generation level by platforms altogether.

Since the platforms with higher within generation market share are more prominent for attracting users to adopt that technology, instead of a simple average, we compute the average of agglomerations points of the platforms (numbers in the horizontal axis of Figure 4) in the same generation weighted by their within generation market share (numbers beside each platform in Figure 4) as $Agg_g = \frac{\sum_{i=1}^{n} Agg_i \,.\, MS_i}{\sum_{i=1}^{n} \sum Agg_i}$. Where Agg_i is the agglomeration point for platform i in generation g and MS_i is corresponding within generation market share. This variable, Agg_g, shows the concentration of all platforms´ activities within each generation (agglomeration point at generation level), while taking the significance of each platform in terms of market share into account. Put differently, it is the point of time that most of the game titles are provided at generation level by platforms altogether—the apex of momentum at the aggregate level. We expect this period, which technology momentum peaks, to coincide with the market tipping point for that technology. To test this coincidence, we illustrate the number of all console unit sales for each generation[21] along with the above computed number and corresponding 99 percent confidence interval. Graphically the market tipping occurs at the point which the adoption rate takes off and experiences a sizable jump. We expect this point to be within the abovementioned interval.

As Figure 5 depicts supporting our prediction, the "takeoffs" or market tipping points for generations 5 and 7 and roughly for generation 6 are within 99 percent confidence interval. However, this is not very evident for generation 4. Replacing this interval with 95 percent confidence interval, standard error, or standard deviation intervals leads to a qualitatively similar pattern (not reported here but available upon request).

[21] Sum of unit sales for all platforms within each generation graphed in median spline

FIGURE 5
Market tipping point for each generation (G=4, 5, 6, and 7) with 99 percent confidence interval



Consistent with the temporal and evolutionary conceptualization of momentum elaborated above, at aggregate level, and considering not just the momentum of a given platform but of an entire system of (competing) platforms, the market tipping point is predicted by the period of time at which the momentum (or energy) of the whole system concentrates. The agglomerated momentum of these platforms pushes the users to overcome their friction of sticking to the previous technology generation and switch to the new one (Katz and Shapiro, 1992, 1994).

DISCUSSION

Sectors such as telecommunications (smartphones), video games (entertainment systems), social networks, and even news (e.g., Craiglist) have witnessed over the past years drastic changes in leadership, with the rise of newcomers, and the fall of dominant firms' technologies despite their huge existing installed user base. The smartphone sector is a paramount example. The pioneer and dominant player in the industry, Nokia, the first to assemble a network of apps developers around Symbian (the operating system powering its devices), has soon lost leadership of the premium segment of the market in favor of BlackBerry, a startup that very quickly gained momentum and the mass of corporate users. Yet, despite this momentum, a new player, Apple, has been able to overcome the disadvantage associated with the lack of installed user base, and quickly erode market share from incumbent players, but only to then see yet another new player, Google, gaining about 80 percent of the whole market. Despite the predictions of existing theory according to which the "excess inertia" (Katz and Shapiro, 1992) associated with the installed user base of a technology would act a self-reinforcing isolating mechanism and limit room in the market for late comers, particularly in network markets, we observe "dethroners" in a range of contexts (Suarez and Kirtley, 2012).

Addressing this phenomenon, we revisit the concept of momentum and inertia as considered in the extant literature of technology adoption and extend the existing theory by disentangling the momentum effect into a static, inertial component, which we refer to as *stock*, and a dynamic component, which we refer to as *novelty*. The focus in prior studies has been prevalently on the static component of momentum, the mainstream logic being that technologies that gain a critical mass of users will obtain further users and eventually end up dominating the whole market thanks to market momentum. Because of this "excess inertia" effect (Katz and Shapiro, 1992), competing technologies that enter the market at later stages, or have a smaller mass of users are inevitably destined to fail.

However, this logic does not account for the possibilities that late entrants might grow their network faster, despite their initial network disadvantage (Suarez and Lanzolla, 2007).

We test these effects in the context of the U.S. video game industry and find a positive effect for both stock and novelty on platform adoption. Yet the dynamic component, novelty, with a substantially stronger impact. We should mention that the relative strength of novelty vis-à-vis stock is more evident when the real-time adoption rate is considered as the dependent variable, rather than the cumulative one (shown in Table 6). This is in line with our aim to reveal the dynamism of technology adoption instead of focusing on a static *frame* of its evolutionary outlook. In particular, cumulative of sales pertain to the static consideration, while the current period unit sales (and market share) relate to the dynamic view.

Our findings, while corroborating previous studies on technology adoption highlighting the importance of inertial effect associated with the stock of complements/size of user base, extend recent work questioning the unconditional dominance of the technology with the largest network (e.g., Lee et al., 2006; Suarez, 2005), the benefits from entering first (e.g., Schilling, 2002, Suarez and Lanzolla 2007; Zhu and Iansiti, 2012), and the winner-take-all outcome (e.g., Cennamo and Santaló, 2013; Lee et al., 2006). This articulation of the momentum, by identifying both the inertial and dynamic aspects, lends more accuracy in assessing technology evolution and competitive dynamics of rival technologies racing for the market, which can help explain several instances in the business world from failures of big platforms in the market to the symbiosis of multiple platforms in the market. In particular, this revisited concept of momentum consistently integrates the “excess inertia” and “insufficient friction” scenarios ascribed by Katz and Shapiro (1992).

We find that our empirical context is more consistent with an “insufficient friction” scenario given the relative prominence of novelty (the velocity component of momentum). Yet, this might not be a unique case. Anecdotal evidence suggests that novelty crucially affects users’ adoption and usage of the platform in many other platform contexts, including social networks, mobile app industry, media and entertainment platforms, and retailing portals among others. For instance, in a C2C portal such as Airbnb, renters value the up-to-date rental ads rather than a diverse number of *abandoned* ones. A full list of diverse, yet idle, rental ads, is not enough to invite customers to adopt/use the platform’s services. The same applies to other platforms such as Youtube (novel videos catch generally more attention from viewers) or Groupon (users are much more interested in novel offerings than “dated” ones). Assessing the weight of the inertial and dynamic components of momentum in different contexts might shed light on important overlooked contingencies that improve our understanding of technology adoption *and* evolution dynamics, and help explain why in some contexts we see “excess inertia” prevailing, thus persistence of incumbent technologies, while in other cases “insufficient friction” gives room to dethroners. Our analysis is a starting point towards this direction, which we hope will stimulate further work.

Limitations and further research

Despite the fact that we find a much stronger impact of novelty than stock on technology adoption, we should acknowledge that this high asymmetry pertains to our specific context. Although we expect to find a similar pattern in other contexts related to entertainment, media and even retailing industries as exemplified earlier, in some other contexts productivity/functionality aspects might be more important (such as in Operating Systems) than the novelty of complements. Further studies should assess to which extent this is the case by analyzing the effects in other industries. Moreover, we assumed that game titles are durable goods but with a strong decay effect. However, we did not explicitly model this aspect; we tried to capture it by estimating various distinct lags in our analysis. Developing a formal model while considering a discount factor value of complements (based on Clements and Ohashi, 2005) is a worthwhile opportunity to accurately estimate the relative strength of inertial versus dynamic effects in different contexts. Moreover, we did not account for the different policies that platform sponsors deploy to attract complementors and stimulate the production of novel complements. We just control empirically for differences across platforms through fixed effects; yet, how precisely these differences contribute to shape the inertial and dynamic component of momentum is an interesting area to investigate. Finally, although we tried to deal with the aforementioned endogeneity concern (stock versus novelty coefficients) with several remedies, through Tables 10 to 13, future analyses with other available instrumental variables is called for increasing the robustness of our results.

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CONCLUSION

Following the growing body of knowledge regarding the platform-mediated industries, this dissertation centers on competitive strategy for two-sided platforms. I attempt to understand how firms in platform-mediated (network) industries respond to the competitive drivers differently than others in conventional ones. The presence of network externalities creates numbers of strategic trade-offs and requires more sophisticated competitive strategies. In particular, in the first and second chapters, I investigate two of these trade-offs in pricing and nonpricing strategies. I look into this topic in the context of airport industries. Modern airports do not serve only airlines and passengers; they also profit from their commercial side— e.g., shops in terminals. The externalities between the airside and commercial side of the airport is an appealing, yet overlooked, opportunity to study airports from a network perspective. Moreover, airports' business models, governance structure, and institutional factors vary considerably in both airside and commercial side. These heterogeneities in addition to data availability for several aspects of airports' business provide me with a worthwhile possibility to pursue my research objectives in this context.

The first chapter addresses the pricing strategy and investigates the case in which both positive indirect and negative direct network effects are of prime importance. The reciprocity of these two effects is less explored in the previous studies. I examine how a firm reacts optimally to an exogenous change in competition within one group of the users by modifying its pricing strategies for both groups. Considering both aforementioned effects, I contribute to the literature and scrutinize an important strategic trade-off in which increasing the size of the network and the installed base of users is not always an optimal strategy. Instead, while keeping the participation of users in the ecosystem *vivid*, firm should avoid congesting the *ecosystem* and secure its customers from detrimental competition. In the context of U.S. airports, I find that within-platform competition on one side increases the price charged to the other side. The same-side price increases only if the platform's capacity is constrained. In response to entry of more airlines, hence the rise of utility in commercial side due to positive network effect, airports extract rent by setting higher prices charged to commercial retailers. Whereas they try to secure airlines, as the critical users of the ecosystem, from negative effect of within-airport competition. However, in capacity-constrained airports, in which the within-group competition among extant airlines is less intense, a high bargaining power for the airports allows them to charge a higher price to the airlines as well. I also analyze the differential impact of an increase in within-platform competition on different business models—two-sided platform versus conventional one-sided—in the same industry. In the former, airports are able to take advantage of the reinforcing effect between airlines and commercial retailers by a cross-subsidization pricing structure. While in the latter, they do not: revenues from airlines and commercial retailers are considered separately for setting the prices. The empirical evidence shows that a two-sided platform model allows airports to cope better with the enhanced within-group competition.

Overemphasizing on arm's length pricing in network industries has been questioned, and it is asserted that other sorts of strategies such as governance and design mechanism should be implemented to assure a sustainable performance. Nevertheless, theorizing about nonpricing strategies is still in its infancy. Contributing to this stream of research, in the second chapter, I study how platforms, by a *noisy* and imperfect design, make the users on one side worse off, while gaining higher profitability from the other side´s users who benefit from this design strategy, which I call *waiting time increase.* I depict how airports, by modifying the layout design of terminals, check-in procedures and the like, lengthen the passengers' waiting time in terminals. Doing so, while passengers and airlines are worse off, the airport increases the probability of purchase from in-terminal shops, hence commercial retailers are better off. I analyze related drivers and contingencies according to airports' governance structure in the commercial side. The results show that airports, once outsource the management of commercial side to third-parties, are more prone to increase waiting time, the higher is the prominence of revenue generation and/or concentration in this side.

In the third chapter, I focus on platform-mediated industries in digital environment. First, I attest how the "get-big-fast" approach for attaining the critical mass of users, igniting the platform, and gaining market momentum has been restricted to a static consideration. I point out that the dynamics of competition diminishes the value of complementary products over time. Accordingly, firms need to update and keep the supply of complementary products *alive*, what I call *novelty* strategies. I revisit the momentum metaphor in technology adoption literature, by combining both mass/variety and velocity/novelty together. In other words, Not only are the variety (stock) of previously supplied complements important but also the velocity of new complements provision (novelty) plays a vital role in obtaining and preserving momentum in the market. I hypothesize and empirically show that, in U.S. video game industry, the effect of the latter on game console adoption is substantially stronger. This has relevant implications for technology adoption and platforms competitive dynamics, which might help to explain the market evolution and why latecomers may dethrone incumbents despite network size disadvantage. New entrants, with small network size, may dethrone the platform with a large stock of complements and installed base of users, if outperform in novelty strategies— the pace of new complements supply. Building on this temporal and evolutionary concept of technology adoption, I also extend this chapter from firm level to technology aggregate level and estimate the tipping point in adoption of new generations of game consoles.

To conclude, my dissertation is an endeavor to shed more light on competitive strategies in platform-mediate industries, and to study the nuanced dynamism and strategic trade-offs specific to two-sided platforms. Although I implement various analyses to verify the results, and to corroborate the theorized mechanisms as much as possible, without reservation, applying different empirical contexts and/or exploiting more detailed data can increase the robustness of the findings and hypotheses. I hope this dissertation, despite all the shortcomings, will trigger future researches in this regard.

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CONCLUSIÓN

Basándose en el creciente conjunto de conocimientos en lo tocante a las industrias medidas por plataformas, esta tesis se centra en la estrategia competitiva de las plataformas bilaterales. Intentamos dilucidar cómo las empresas en industrias mediadas por plataformas (redes) reaccionan a los estímulos competitivos de forma distinta a las convencionales. La presencia de externalidades de red produce una serie de compensaciones estratégicas y requiere unas estrategias competitivas más sofisticadas. Concretamente, en los dos primeros capítulos investigamos las compensaciones en las estrategias tarifarias y no tarifarias. Examinamos esta cuestión en el contexto de la industria aeroportuaria. Los aeropuertos modernos no sólo atienden a las aerolíneas y los pasajeros, sino que también se benefician de la vertiente comercial, esto es, las tiendas en las terminales. Las externalidades entre la vertiente aeronáutica y la comercial de un aeropuerto ofrecen una atractiva –si bien ignorada– oportunidad para estudiar los aeropuertos desde una perspectiva de red. Y no sólo eso, los modelos de negocio de los aeropuertos, sus estructuras de gestión y los factores institucionales varían sustancialmente entre la vertiente aeronáutica y la comercial. Estas heterogeneidades, junto con la disponibilidad de datos con respecto a diversos aspectos del negocio aeroportuario, nos proporciona la valiosa posibilidad de cumplir los objetivos de nuestra investigación en ese contexto.

El primer capítulo aborda la estrategia tarifaria e investiga el caso en el que los efectos de red positivos indirectos y los negativos directos revisten la mayor importancia. La reciprocidad de estos dos efectos es un aspecto que ha tenido menor relevancia en los estudios anteriores. Examinamos la forma en que una compañía reacciona de forma óptima a un cambio exógeno en la competencia dentro de un grupo de usuarios al modificar sus estrategias tarifarias para ambos grupos. Al tomar en consideración los dos efectos antedichos, contribuimos a los estudios y analizamos una importante compensación, en virtud de la cual el incremento en el tamaño de la red y la base de usuarios no siempre es una estrategia óptima. En lugar de eso, mientras mantiene una participación *viva* de los usuarios en el ecosistema, la empresa debe evitar una congestión del *ecosistema* y proteger a sus clientes de una competencia perjudicial. En el contexto de los aeropuertos estadounidenses, advertimos que la competencia intra-plataforma en una vertiente incrementa la tarifa cobrada en la otra. La tarifa dentro de la misma vertiente sólo aumenta cuando se restringe la capacidad de la plataforma. Como reacción a la entrada de un número mayor de aerolíneas –lo cual redunda en una mayor utilidad en la vertiente comercial debido a los efectos positivos de red– los aeropuertos obtienen ingresos elevando las tarifas cobradas a los vendedores. Paralelamente, intentan proteger a las aerolíneas –en calidad de usuarios críticos del ecosistema– del efecto negativo de la competencia dentro del aeropuerto. No obstante, en los aeropuertos de capacidad limitada, en los que la competencia intragrupal entre las aerolíneas existentes es menos intensa, estos tienen una mayor capacidad negociadora que les permite cobrar tarifas más elevadas también a las aerolíneas. También analizamos el impacto diferencial del incremento de la competencia intra-plataforma en diversos modelos de negocio –plataformas bilaterales y plataformas unilaterales convencionales– en la misma industria. En las primeras, los aeropuertos pueden aprovecharse del efecto reforzador entre las aerolíneas y los vendedores por medio de una estructura tarifaria de subvención cruzada. En cambio, en las segundas no lo hacen: los ingresos generados por las aerolíneas y los vendedores se consideran de forma separada a la hora de fijar las tarifas. Las pruebas empíricas nos muestran que el modelo de plataforma bilateral permite a los aeropuertos afrontar mejor el aumento en la competencia intragrupal.

Se ha cuestionado el exceso de importancia atribuido a la tarificación en las industrias de red en régimen de plena competencia, y se reivindica la necesidad de aplicar otras estrategias como la gobernanza y el mecanismo de diseño para alcanzar un rendimiento sostenible. No obstante, las teorías acerca de las estrategias no tarifarias aún se encuentran en una fase embrionaria. A modo de contribución a esta rama de la investigación, en el segundo capítulo estudiamos la forma en que las plataformas, por medio de un diseño *ruidoso* e imperfecto, empeoran las condiciones de los usuarios en una vertiente mientras que obtienen una mayor rentabilidad de los usuarios de la otra, que se benefician de esta estrategia de diseño; lo hemos denominado *incremento en el tiempo de espera*. Analizamos la forma en que los aeropuertos, al modificar el diseño de las terminales, los procedimientos de facturación y otros aspectos similares, alargan el tiempo de espera de los pasajeros en sus instalaciones. Al hacer tal cosa, si bien los pasajeros y las aerolíneas salen peor parados, el aeropuerto incrementa la rentabilidad de las compras en las tiendas de las terminales, lo cual beneficia a los vendedores. Analizamos los estímulos y contingencias relacionados entre sí de acuerdo con la estructura de gobernanza del aeropuerto en su vertiente comercial. Los resultados indican que, una vez que los aeropuertos externalizan la gestión de la vertiente comercial, son más proclives a incrementar el tiempo de espera, y que la preeminencia de la generación de ingresos y/o la concentración en esta vertiente es mayor.

En el tercer capítulo nos centramos en las industrias mediadas por plataformas en el entorno digital. En primer lugar, constatamos que el enfoque de “ganar volumen rápidamente" para alcanzar una masa crítica de usuarios con el consiguiente arranque de la plataforma e impulso de mercado ha quedado limitado a una consideración estática. Señalamos que las dinámicas competidoras reducen el valor de los productos complementarios a lo largo del tiempo. Por consiguiente, las empresas necesitan actualizar y mantener *vivo* el suministro de productos complementarios, lo que hemos bautizado como estrategias de *novedad*. Revisamos la metáfora del impulso en los estudios de adopción de nuevas tecnologías combinando masa/variedad y velocidad/novedad. En otras palabras, no sólo es importante la variedad (existencias) de los complementos suministrados anteriormente, sino que la velocidad de suministro de nuevos complementos (novedad) desempeña un papel vital para alcanzar y mantener el impulso en el mercado. Hipotetizamos y mostramos empíricamente que, en la industria del videojuego en EEUU, el efecto de lo segundo en la adopción de videoconsolas es notablemente más fuerte. Esto conlleva importantes implicaciones para las dinámicas de competencia entre plataformas y la adopción de nuevas tecnologías, lo cual puede contribuir a explicar la evolución del mercado y la razón de que los recién llegados puedan defenestrar a los ya presentes a pesar de la desventaja que supone el tamaño de red. Nuevos participantes, con un tamaño de red reducido, pueden defenestrar a plataformas con grandes existencias de complementos y una gran base de usuarios, siempre y cuando demuestren una mayor eficiencia en sus estrategias de novedad (el ritmo de suministro de nuevos complementos). Basándonos en este concepto temporal y evolutivo de la adopción tecnológica, también ampliamos este capítulo desde el nivel de las compañías hasta el nivel de la agregación tecnológica, y estimamos el punto de inflexión en la adopción de nuevas generaciones de videoconsolas.

A modo de conclusión, esta tesis constituye un intento de arrojar más luz sobre las estrategias competitivas de las industrias mediadas por plataformas, y de estudiar el sutil dinamismo y las compensaciones estratégicas propias de las plataformas bilaterales. Aunque aplicamos varios análisis para verificar los resultados, y para certificar en la medida de lo posible los mecanismos teorizados, cabe afirmar sin reservas que la aplicación de contextos empíricos distintos y/o la utilización de datos más detallados puede dotar de mayor robustez a los hallazgos e hipótesis. Confiamos en que esta tesis, a pesar de todas sus limitaciones, motivará investigaciones adicionales