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RESEARCH PAPER

Security-Induced Lock-In in the Cloud

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Abstract Cloud services providers practice security-induced lock-in when employing cryptography and tamper-resistance to limit the portability and interoperability of users' data and applications. Moreover, security-induced lock-in and users' anti-lock-in strategies intersect within the context of platform competition. When users deploy anti-lock in strategies, such as using a hybrid cloud, a leader–follower pricing framework increases profits for cloud services providers relative to Nash equilibrium prices. This creates a second-mover advantage, as the follower's increase in profits exceeds that of the leader owing to the potential for price undercutting. By contrast, introducing or enhancing security-induced lock-in creates both an increase in profits and a first-mover advantage. Cloud services providers therefore favor security-induced lock-in over price leadership. More broadly, we show why standardization of semantics, technologies, and interfaces is a nonstarter for cloud services providers.

Keywords Cloud services providers · Cybersecurity · Lock-in · Switching costs · Anti-lock-in strategies · Platform economics

1 Introduction

Cloud services providers (CSPs) convert users' fixed IT costs into variable ones through a pay-as-you go system that is finely granular and readily available. For small and medium enterprises and start-ups, cloud benefits include increased availability and mobility, and on-demand capacity and scalability, thereby reducing entry barriers. Larger users can also fully capitalize on the cloud's potential for ubiquity and increased collaboration. The cloud services stack is divided into Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS), and Software-as-a-Service (SaaS). Worldwide end-user spending on cloud services is expect to grow from \$145.3 billion in 2017 to \$362.3 billion in 2022 (Statistica.com 2021).

CSPs exhibit substantial capacity requirements (e.g., server farms) and low marginal costs from virtualization. This leads to the commodification of services at any given layer in the stack. Yet semantics, technologies, and interfaces are not standardized across CSPs. Cloud computing is not a simple matter of plug and play. In addition, lack of standardization across CSPs raises current and prospective users' antennae to lock-in barriers to switching. Formally, the *vendor lock-in problem* in cloud computing exists when users' dependency upon their CSP's proprietary configurations create switching costs limiting users' business opportunities. CSP lock-in stems from users' lack of portability and interoperability. *Portability* refers to the degree that data and applications are in a compatible format, giving users the ability to migrate to an alternative CSP and do so with minimal effort. Portability includes the means to verifiably remove and delete data housed in a CSP (Hogan et al. 2011). *Interoperability* refers to users' ability to exchange assets seamlessly across CSPs (interoperate) (Pectu 2011).

This study recognizes the paramount nature of data as a business asset. Its focus is on *data lock-in* arising from CSP users' difficulties in both migrating data and doing so without disrupting its availability. Data lock-in persists as a

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major obstacle to portability and interoperability (Armbrust et al. 2010; Subramanian and Jevaraj 2019). It has implications for users' business continuity and disaster recovery planning (Knipp et al. 2016). If a CSP fails for economic or financial reasons, organizational data may be unrecoverable or access to it delayed. Moreover, no CSP is 100% reliable. Businesses locked into a CSP are vulnerable to downtime.

Lock-in is a vulnerability rather than a threat. It is a security issue because CSPs store data in a proprietary way. Indeed, users do not own the facilities where CSPs store their sensitive data, have limited control over it, and may not even know the facilities' exact physical locations. Furthermore, a "walled garden" facilitates lock-in. Indeed, Anderson (2004, 2020) contends that lock-in encourages IT platforms to add security benefiting themselves rather than users. Adding security mechanisms such as cryptography and tamper-resistance also controls compatibility. "Sometimes security solutions might be focused on other objectives than security, for instance, on achieving consumer lock-in" (Asghari et al. 2016, p. 269). Following Opara-Martins et al. (2016, p. 2), "it can be concluded that cloud interoperability (and data portability) constraints are potentially results of an anticompetitive environment created by offering services with proprietary standards." Lookabaugh and Sicker (2004) call this *security-induced lock-in*.

To the best of our knowledge, this paper is the first to theoretically examine this facet of CSP security, which differs from how security against malicious threats (cybersecurity) works to keep users from switching (Arce 2020a; Sen et al. 2020). There is a difference between users' decision to switch owing to cyber (in)security versus users' (in)ability to switch owing to security-induced lock-in. Security-induced lock-in is a variation on Young and Yung's (1996) classic theme that cryptography can be used to lower users' security by maintaining control over a critical resource.

This paper investigates security-induced lock-in within the context of CSP platform competition. The term platform competition comes from the economics of two-sided markets (e.g., Parker and Van Alstyne 2005; Tatsumoto 2021); it applies equally to IaaS and SaaS in addition to PaaS. As lock-in is a competitive phenomenon, it makes sense to investigate lock-in within CSPs' competitive environment. Indeed, when characterizing CSP cybersecurity against malicious threats within the context of platform competition, Arce (2020a) shows that cybersecurity both determines a CSP's competitive environment (e.g., monopolistic versus imperfectly competitive) and is determined by the competitive environment. Sen et al. (2020) derive the relationship between cybersecurity and whether a software market is monopolistic or perfectly competitive. These studies provide context for the current analysis, which theoretically investigates the synergy between security, lock-in, and leadership in CSP platform competition. It contributes to the literature quantifying and qualifying Anderson's (2001) discourse on how economic considerations make information security hard.

Security-induced lock-in is a form of strategic IT investment limiting users' ability to switch CSPs that themselves engage in platform competition. Alternatively, Barua et al. (1991) examine strategic IT investment for obtaining a competitive advantage by improving users' quality of service. They focus on the non-price implications of combining services as a means to strategically increase quality. By contrast, security-induced lock-in creates pricing power and data access barriers that are detrimental to users. Moreover, users are not passive with respect to the effects of lock-in; they both anticipate the effect of lock-in on future prices and implement anti-lock-in strategies. An example of an anti-lock-in strategy is a hybrid cloud where organizationally critical data is kept in-house by the user.

This research considers a 2-CSP game of pricing competition and data lock-in where users also determine the degree of lock-in via anti-lock-in strategies. At the same time, data lock-in is modeled similarly to how Gordon and Loeb (2002), Ruan (2017), and Arce (2018) probabilistically model security and vulnerability to malicious threats, in that CSP competition and users' anti-lock-in strategies co-determine the *probability of access to data* (Razavian et al 2013). The presence of users' anti-lock-in strategies implies lock-in is neither complete, as is usually the case in economic models of lock-in, nor completely absent, as is the case for users who do not adopt a CSP for fear of lock-in. The characterization of CSP pricing strategies, lock-in strategies, and users' switching costs and anti-lock-in strategies occurs under the auspices of CSP platform competition.

The resulting game additionally differs from prior treatments of lock-in because lock-in is security-induced and determined by users' anti-lock-in strategies and platform competition between CSPs. Under such circumstances the CSPs' prices are strategic complements. Yet they are inefficient relative to the CSPs' joint profit-maximizing prices. Both CSPs' profits increase via price leadership. Hence, price leadership is a means to counter users' anti-lock-in strategies. A coordination problem exists, however, as the follower benefits more than the leader; i.e., a second-mover advantage occurs owing to the possibility of undercutting. It is akin to Cloud 1.0, with its emphasis on pay-as-you-go subscription services that shift users' fixed IT costs to CSPs.

In contrast to the second-mover advantage for the case of price leadership, the findings here establish conditions for a first-mover advantage in security-induced lock-in.

Consequently, standardization is a non-starter for CSPs. The conditions critically depend on the differences in a CSP's profit sensitivity to their rival's price. Game-theoretically, price competition is characterized in terms of strategic complements, a property pertaining to the CSPs' best reply functions. Cross-price profit sensitivities are instead a matter of the degree that CSP prices are plain complements, a property pertaining to the CSPs' profit functions (Eaton and Eswaran 2002). These conditions point toward the evolution of Cloud 2.0 and the transformational potential of cloud computing, with CSPs competing beyond price by adding to the value proposition of users.

As a broader contribution, security-induced lock-in is an example of an interoperability barrier to competition. "If a platform is required to be interoperable, that opens access to the platform, that lowers entry barriers and then, suddenly, you have more competition," implying that interoperability is a powerful regulatory tool (Scott Morton 2021). This study characterizes the power of interoperability regulation in terms of the relative effects of user's anti-lock-in strategies versus security-induced lock-in by CSPs. It also differs from how restricting barriers to data portability at the consumer level functions as an anti-lock-in strategy that changes the competitive environment of platforms whose business model is based on transforming data into revenue (e.g., Wohlfarth 2019). The users in this study are firms contracting with CSP services for their employees and proprietary data rather than users as individual consumers with personal data.

2 The Nature of CSP Lock-In

There is widespread recognition of lock-in in the cloud, however, few models address it head on. Klemperer (1995) provides an overview of the general economic literature surrounding lock-in and switching costs. Complementary surveys include Padilla (1991), Farrell and Klemperer (2007), and Villas-Boas (2015). Shapiro and Varian (1999) and Varian (2004) address lock-in, switching costs, and information technology. Lookabaugh and Sicker (2004) discuss four categories of security-induced lock-in: proprietary security protocols; open security protocols; proprietary extensions to open security protocols; and intellectual property rights and other legal constructs.

Users endow CSPs with quasi-monopoly power. Recognizing this, users fear the well-known bargain-then-rip-offs phenomenon associated with vendor-user relationships in the presence of lock-in. CSPs attempt to allay users' fears with future price commitments. The problem with the pay-as-you-go nature of CSP subscriptions is price commitments do not fully capture the user-CSP value proposition. CSPs introduce fees as a form of cost-of-service-creep; implement a razors-and-blades strategy with respect to add-on services and components; and also vary quality of service in ways users may be unable to detect. The effects are similar to CSPs practicing a form of price discrimination between new and locked-in users. The end result is akin to a CSP's inability to commit beyond its initial price at the time of adoption, with this as our modeling strategy. Consequently, a CSP cannot create switching costs by committing to a lower second-period price for continuing users, as is the case in Caminal and Matutes (1990). Instead, security-induced lock-in creates switching costs via barriers to interoperability and portability.

Lock-in increases CSPs' pricing power. But users are not passive observers to the process; they act strategically to protect themselves from its adverse effects and use it to their advantage when possible (Shapiro and Varian 1999). In our analysis, foresighted users carefully balance the tradeoff between the benefits of lock-in; e.g., more powerful implementation when the CSP couples tightly with the user's business requirements; with the costs, which are most closely associated with increasing prices over time.

Switching costs also arise due to learning effects. It takes time for a user's employees to learn the proprietary aspects of their CSP. Any time required to learn the proprietary aspects of the next best alternative CSP is a switching cost. Shapiro and Varian (1999) regard the total switching costs of locked-in users as the value of an IT platform's installed base. As users' experience with their CSP increases, their benefits grow and become specific to the CSP. Switching to a rival results in lost learning effects. Our model recognizes this.

Network effects as well work against switching CSPs. Network effects (network externalities) occur when the benefits of using a CSP rise with the number of users of the CSP. Opara-Martins et al. (2016) find that organizations with 250 + employees realize significant benefits from increased collaboration through CSPs. Users' switching costs are increased by the presence of network effects. This is reflected in our model by an increased valuation for continuing with a CSP in the second period as compared to a lower valuation if the user switches CSPs. Hence, CSPs face a no-switching constraint that accounts for both the potential for switching and its impact on users. Within the context of platforms-as-two-sided-markets, Lee (2014) proposes the no-switching criterion to characterize non-monopolistic platform equilibria on the complementor (e.g., app) side when platform-complementor contracts are contingent on the number of complementors. Arce (2020a) subsequently employs the no-switching criterion to characterize the symbiotic relationship between cybersecurity and CSP market structure on the user side under platform competition, when cybersecurity attacks are based on the number of users (market share). As CSPs are platforms, and security-induced-lock-in and anti-lock-in strategies affect switching costs, this equilibrium criterion is invoked here as well. To wit, when platforms' strategies satisfy the no-switching criterion, the competitive environment can allow for multiple platforms rather than being monopolistic. The no-switching criterion therefore lies at the foundation of analyzing strategic interaction amongst two or more CSPs, as no level of the CSP stack is monopolistic. In particular, for multiple CSPs to persist within a level of the CSP stack, each CSP's pricing strategy must satisfy a no-switching constraint in equilibrium.

Technically, the no-switching criterion is related to the concept of coalition-proof Nash equilibrium (Bernheim et al. 1989). This refinement requires a CSP's equilibrium strategies to be stable against a credible deviation from the equilibrium by a subset of players (Greenberg 1989; Kahn and Mookherjee 1992). In the present context, this implies that a CSPs strategies rule out losing a subset (coalition) of its users owing to alternative pricing policies of a rival CSP. Effectively, under this criterion the CSPs' strategies ensure that no "tipping" occurs that would otherwise lead to monopoly. As such, the resulting platform competition need not be winner-take-all or winner-take-most, but is instead consistent with the reality of multiple CSPs competing within the cloud stack. By contrast, much of the extant literature on platform economics assumes platform-as-monopoly and yet we know that this is not the case in the CSP market. Hence, another contribution of this analysis is placing CSPs within a non-monopolistic context.

The discussion thus far substantiates the need for a model of CSP pricing and security-induced lock-in within the context of platform competition. Such a model requires (i) switching costs reflecting users' learning and network effects with their CSP; (ii) lock-in strategies by CSPs in platform competition; (iii) users adopting anti-lock-in strategies to keep their CSP options open; and (iv) no-switching equilibrium constraints as a means of capturing the strategic effects of platform competition among CSPs. The following section introduces a corresponding extensive form game.

3 The Model

The players are the two CSPs and N users. CSP i's strategies are its prices in the first and second periods, (P_{i1}, P_{i2}); $i = 1, 2$. In addition, CSP i's lock-in strategy partially determines the value of lock-in variable, $\lambda_i \in [0, 1]$: its users' degree of data access if switching CSPs. When $\lambda_i = 0$, the user is completely locked-in; if $\lambda_i = 1$, the user is not locked-in whatsoever. Given the first-period prices for the two CSPs, P_{11} and P_{21}, the number of CSP 1 users is $n(P_{11}, P_{21})$, and the number of CSP 2 users is its complement, $N - n(P_{11}, P_{21})$. Two standard assumptions about $n(P_{11}, P_{21})$ hold: (i) $n(P_{11}, P_{21})$ is twice-continuously differentiable over all its arguments, and (ii) when both CSPs' second-period prices, P_{12} and P_{22}, satisfy no-switching (or participation) constraints, then $n(P_{11}, P_{21})$ and $N - n(P_{11}, P_{21})$ carry over to the second period. This is why we write $n(P_{11}, P_{21})$ as a form of shorthand notation rather than $n((P_{11}, P_{12}), (P_{21}, P_{22}))$. However, we do identify and discuss the effects of P_{12} and P_{22} on $n(\cdot, \cdot)$ and P_{11} and P_{21} below.

When first-period users carry over to the second period, the CSPs' profits (payoffs) are

$$\Pi_1 = n(P_{11}, P_{21})P_{11} + n(P_{11}, P_{21})P_{12} - FC_1;$$
$$\Pi_2 = [N - n(P_{11}, P_{21})]P_{21} + [N - n(P_{11}, P_{21})]P_{22} - FC_2.$$

CSP i's profit is the sum of its first and second period revenues less its fixed costs, FC_i. The origins of many CSPs stem from employing excess capacity used to support their firm's primary business, such as servers for AWS, or the ability to scale at or near zero marginal cost, as is the case for SaaS. This specification of a CSP's profit function is also in keeping with users shifting fixed IT costs to CSPs. A CSP's marginal cost is equal to zero unless maximum capacity is reached, with the CSP business model premised on leveraging capacity to preclude such an event. Specifically, multi-tenancy facilitates guaranteed performance through a virtuous cycle where more users implies both more funds for capacity investment and less variation in overall average demand. This in turn implies the CSP needs less capacity and can charge lower prices that lead to more users.

An alternative interpretation of the payoff functions is CSPs are, effectively, revenue-maximizers, as is the case for the platforms investigated in Wohlfarth (2019). Such an interpretation of CSP behavior is independent of assumptions about the CSPs' cost structure.

No discounting occurs for users or CSPs. In multi-period pricing games with switching costs, discount factors are a proxy for how forward-looking (price sensitive) users are to the CSP strategy of enticing users with a low first-period price followed by a higher second-period price once users are locked in. Forward-looking users recognize this potentiality and are less price sensitive in the first period. CSPs recognize user's price insensitivity, consequently, first-period prices are higher when users are forward-looking. Discounting is replaced by the probability that a user can access their data when attempting to switch CSPs, $\lambda_i \in [0, 1]$, which is an alternative forward-looking phenomenon. In contrast to discounting, which is an exogenous preference, λ_i is determined by users' anti-lock-in strategies and platform competition between CSPs.

For example, Fonash and Schneck (2015) note that the presence of a walled garden may induce users to acquire additional products and services from a single CSP because the nature of the shared security problem is known. Consequently, the value of λ_i decreases: "This commits the user to the deployed (CSP) solution even if a demonstrably more useful or functional alternative exists" (p. 46). For example, if the CSP uses homeomorphic encryption, then users can process their data without the key and may base essential applications on this relationship with their CSP. At the same time, CSP possession of the key inhibits data portability. Indeed, industry studies reveal, "CSPs can use data preservation, in particular, as a means of vendor lock-in by making data transfer to another service time-consuming or cumbersome" (Lynn 2021, p. 34). In anticipation of data lock-in, Raj et al. (2021) recommend manual data exportation into a standard format on a regular basis. This increases the value of λ_i. Other *anti-lock-in strategies* include keeping proprietary data in-house, resulting in a hybrid cloud or layered architecture; using a CSP broker or cloud management provider; monitoring CSP updates and assessing their impact on lock-in; employing enterprise service bus middleware for cloud-user integration that facilitates decoupling; or developing data export functionality on one's own. Opting for a CSP with standard interfaces and APIs, employing standard open security protocols, ensuring that all data can be exported via open file formats and platform-independent language are also possibilities that increase λ_i.

More broadly, lock-in occurs due to unique implementations in semantics, technologies, and interfaces adopted by different CSPs, which hinders user portability and interoperability.

> The lock-in situation is evident in that applications developed for specific cloud platforms (e.g., Amazon EC2, Microsoft Azure), cannot easily be migrated to other cloud platforms and users become vulnerable to *any* changes made by their providers … The degree to which lock-in critically affects an organization's business application and operation in the cloud cannot be overemphasized or underestimated (Opara-Martins et al. 2016, pp. 2, 8).

Such circumstances decrease the value of λ_i.

At the extremes, $\lambda_i = 0$ if a user pushes all of its chips in with a CSP in order to ensure interoperability under their CSP's proprietary cybersecurity solutions umbrella. By contrast, $\lambda_i = 1$ if the two CSPs operate in the same cybersecurity ecosystem or federation. Most users and CSPs operate in between these extremes, with $\lambda_i \in (0, 1)$ being the focus of this study.

Users select a CSP in the first period and decide whether to continue with the CSP in the second period. Users' payoffs are the sum of their net benefits in each period (again, no discounting). A user adopting CSP '*i*' in period 1 obtains net benefit $V - P_{i1}$. The absence of an index on users' initial reservation value, V, of their CSP is intentional. Users' initial impetus for adopting a CSP is to transform fixed IT capital expenses into pay-as-you-go variable operating costs. Hence, V is the initial savings in fixed IT capital expenses irrespective of the CSP adopted.

By contrast, a user continuing with CSP '*i*' in the second period receives benefit V_i, where $V_i \in (V, \infty)$. Specifying $V_i > V$ is consistent with accruing learning and network effects when continuing with a CSP. User heterogeneity exists at the CSP level in the second period, thereby implying differences in users' two-period valuation for choosing CSP '*i*' when continuing with CSP '*i*.'

A subtle but important point is a user who switches CSPs in period 2 gets benefit V because no learning effect carries over to the new CSP. Given users are now in the first period of their relationship with newly-adopted CSP '*j*,' they pay P_{j1}. In other words,

$$\text{User } i\text{'s second-period expected payoff} = \begin{cases} V_i - P_{i2}, & \text{if continues with CSP } i; \\ \lambda_i V - P_{j1}, & \text{if switches to CSP } j \neq i. \end{cases}$$

Switching costs are captured by this model through the inequalities $\lambda_i V \leq V < V_i$. The resulting dynamics are not commonly present in models of lock-in. First, users experience learning effects when continuing with a CSP, $V < V_i$, an *advantage* of lock-in owing to switching cost $V_i - V$. Moreover, economists often refer to the degree to which network externalities contribute to V_i exceeding V as a *collective switching cost* (Crémer and Biglaiser 2012).[1] Second, the switching payoff, $\lambda_i V < V_i$, or cost $V_i - \lambda_i V$, imparts a multiperiod flavor. It is as if a switching user induces another subgame where it selects the other CSP. Hence, we solve a stage game where users have the potential to switch, but in equilibrium they do not switch. That is, the switching subgame is not reached because the equilibrium satisfies the *no-switching constraint*:

$$\lambda_i V - P_{j1} \leq V_i - P_{i2}.$$

This criterion is akin to Shaked and Sutton's (1984) technique for deriving the unique solution to Rubinstein's (1982) alternating offers bargaining model by focusing on the subgame perfect Nash equilibrium where the initial offer is accepted. Their initial-offer-accepted constraint puts downward pressure on the initial proposer's

[1] Here the cloud network effect is collectively *within* user groups, as identified by Opara-Martins, Sahandi, and Tian (2016), rather than between user groups.

bargaining share. Consequently, the subgame where the initial offer is rejected is not reached. Here, in recognizing that, in reality, users switch CSPs, a no-switching equilibrium constraint formalizes how the potential for switching puts downward pressure on a CSP's second-period price. This in turn affects the characterization of the CSPs' equilibrium prices in both periods. The advantage is the no-switching constraint places our analysis within the context of CSP platform competition rather than CSP platform-as-monopoly.

The timing of the game reflects the above description. The stage game consists of two periods. In the first period, CSPs set initial prices and users decide which CSP to adopt. CSPs again set prices in the second period and users decide whether to continue with their CSP or to switch. Following Klemperer (1995), endogenizing switching costs requires inserting an initial ('zeroth') period determining the degree of lock-in prior to the stage game. A major difference between the present analysis and other analyses of switching costs is switching cost manipulation is typically considered to be the purview of firms alone (Salies 2012). The contribution here is (i) users employ anti-lock-in strategies; (ii) lock-in takes an alternative form because it is security-induced; and (iii) no-switching constraints incorporate learning and direct network effects. Together, the three phenomena are specific to the user-CSP relationship under platform competition. Finally, in recognizing Shapiro and Varian's (1999) principle that the potential for lock-in necessitates participants to look ahead and reason back, the solution concept used is subgame perfect Nash equilibrium (SPNE); i.e., backward induction. In particular, this implies that when deciding on a CSP in period 1, a user not only takes into account each CSP's period 1 price, but also correctly anticipates the prices each CSP charges in period 2.

4 Benchmark Scenario: Platform Competition when Users are Locked-In

In the benchmark scenario users are locked into their CSP in the second period. Variables in this section have an overbar to distinguish them from the general case. When users are locked-in, $\overline{\lambda}_i = 0, i = 1, 2$.

Solving the game by SPNE means the second period is solved first. As in the first period a CSP cannot commit to a price in the second period, in the second period each CSP sets its price to maximize its profit. Given $\overline{\lambda}_i = 0$, instead of facing a no-switching constraint, the CSP must satisfy its users' participation constraint. For CSP 1,

$$\max_{\overline{P}_{12}} n(\overline{P}_{11}, \overline{P}_{21}) \cdot \overline{P}_{12} \quad s.t. \quad \underbrace{0 \le V_1 - \overline{P}_{12}}_{\substack{\text{users' participation} \\ \text{constraint}}} .$$

Lock-in implies $n(\overline{P}_{11}, \overline{P}_{21})$ carries over to period 2. This yields $\overline{P}_{12} = V_1$.

In the first period CSP 1 selects $\overline{P}_{11}$ to maximize Π_1:

$$\begin{aligned} &\max_{\overline{P}_{11}} n(\overline{P}_{11}, \overline{P}_{21}) \cdot \overline{P}_{11} + n(\overline{P}_{11}, \overline{P}_{21}) \cdot \overline{P}_{12} - FC_1 \\ &\quad = \max_{\overline{P}_{11}} n(\overline{P}_{11}, \overline{P}_{21}) \cdot \overline{P}_{11} + n(\overline{P}_{11}, \overline{P}_{21}) \cdot V_1 - FC_1. \end{aligned}$$

Suppressing the arguments in $n(P_{11}, P_{21})$, CSP 1's first-order condition is

$$\begin{aligned} &\frac{\partial \Pi_1}{\partial \overline{P}_{11}} = \frac{\partial n}{\partial \overline{P}_{11}} \cdot \overline{P}_{11} + n + \frac{\partial n}{\partial \overline{P}_{11}} \cdot V_1 = 0 \Rightarrow \\ &\quad n = -\frac{\partial n}{\partial \overline{P}_{11}} \cdot (\overline{P}_{11} + V_1) \end{aligned} . \tag{1}$$

An interior solution ($n > 0$) requires $\frac{\partial n}{\partial \overline{P}_{11}} < 0$; i.e., the number of users satisfies the law of demand. From the characterization of n given by Eq. (1),

$$\begin{aligned} &\frac{\partial n}{\partial \overline{P}_{11}} = -\frac{\partial n}{\partial \overline{P}_{11}} - \frac{\partial^2 n}{\partial \overline{P}_{11}^2} \cdot (\overline{P}_{11} + V_1) \Rightarrow \\ &\frac{\partial n}{\partial \overline{P}_{11}} = -\frac{1}{2} \cdot \frac{\partial^2 n}{\partial \overline{P}_{11}^2} \cdot (P_{11} + V_1) \end{aligned} . \tag{2}$$

It follows that $\frac{\partial n}{\partial \overline{P}_{11}} < 0$ requires $\frac{\partial^2 n}{\partial \overline{P}_{11}^2} > 0$. User demand is convex. Furthermore, the first-period elasticity of demand is

$$\varepsilon^n_{\overline{P}_{11}} = \left| \frac{\partial n}{\partial \overline{P}_{11}} \cdot \frac{\overline{P}_{11}}{n(\overline{P}_{11}, \overline{P}_{21})} \right| = \frac{\overline{P}_{11}}{\overline{P}_{11} + V_1} = \frac{\overline{P}_{11}}{\overline{P}_{11} + \overline{P}_{12}}.$$

First-period demand is inelastic ($\varepsilon^n_{\overline{P}_{11}} < 1$). Price insensitivity is due to users looking ahead and reasoning back ($\overline{P}_{12}$ is in the denominator of $\varepsilon^n_{\overline{P}_{11}}$), thereby keeping CSPs from duping users with a low first-period price.

Finally, if no learning effects are present, then $V_1 = V_2 = V$. Price competition without product differentiation ensures neither CSP makes excess profits:

$$\begin{aligned} &\Pi_i = n_i(\overline{P}_{i1}, \overline{P}_{j1})\overline{P}_{i1} + n_i(\overline{P}_{i1}, \overline{P}_{j1})V - FC_i = 0 \Rightarrow \\ &\overline{P}_{i1} = \frac{FC_i}{n_i(\overline{P}_{i1}, \overline{P}_{j1})} - V. \end{aligned}$$

A CSP's first-period price equals its average fixed cost less its second-period revenue.

5 Imperfect Data Lock-In

Here, the general game where $\lambda_i \in (0, 1)$ is solved. Backward induction implies the second period is solved first.

Once again, in the first period the CSP cannot commit to a price in the second period. Each CSP sets its second-period price subject to a *no-switching constraint* for users. Specifically, the no-switching constraint accounts for the probability, λ_i, of a user accessing its data to switch CSPs. In addition, when the no-switching constraint supersedes the need for a participation constraint for users, CSP 1's pricing problem becomes

$$\max_{P_{12}} n(P_{11}, P_{21}) \cdot P_{12} \quad s.t. \underbrace{\lambda_1 V - P_{21} \leq V_1 - P_{12}}_{\text{users' no-switching constraint}}.$$

For the no-switching constraint to supersede the participation constraint it must be the case that $\lambda_1 V - P_{21} > 0 \Rightarrow \lambda_1 > P_{21}/V$; otherwise, $\lambda_1 V - P_{21} \leq 0$, implying the participation constraint is instead binding, and the benchmark model applies. Similarly, for CSP 2 it implies $\lambda_2 > P_{11}/V$. Alternatively, if the inequalities do not hold the CSPs can price as if $\lambda_1, \lambda_2 = 0$.

Result 1. *If users' probability of data access falls below a certain threshold, $\lambda_1 \leq P_{21}/V$ and $\lambda_2 \leq P_{11}/V$, then CSPs can price as if users are locked-in.*

As the context of this study is platform competition, we turn to the case where the conditions in Result 1 are reversed. Hence, the no-switching constraints apply. Solving the no-switching constraint for P_{12}[2]:

$$P_{12} \leq V_1 - \lambda_1 V + P_{21}.$$

A similar no-switching constraint for CSP 2 yields P_{22}:

$$P_{22} \leq V_2 - \lambda_2 V + P_{11}.$$

When the no-switching constraints bind, *second-period prices are lower under imperfect lock-in*: $\overline{P}_{i2} > P_{12}$. Imperfect lock-in implies CSPs price strategically in the second period. Whereas users' consumer's surplus, $V_i - \overline{P}_{i2}$, is zero under perfect lock-in, it is positive, $V_i - P_{i2} > 0$, under the price competition implied by imperfect lock-in.

5.1 First-Period Best Replies

Substituting the solutions for second-period prices, P_{12} and P_{22}, into the two-period profit functions for each CSP,

$$\Pi_1 = n(P_{11}, P_{21})P_{11} + n(P_{11}, P_{21})[V_1 - \lambda_1 V + P_{21}] - FC_1;$$
$$\Pi_2 = (N - n(P_{11}, P_{21}))P_{21} + (N - n(P_{11}, P_{21}))[V_2 - \lambda_2 V + P_{11}] - FC_2.$$

[2] The upper bound on P_{12}, $V_1 - \lambda_1 V + P_{21}$, is positive. A negative upper bound results if $\lambda_1 > (V_1 + P_{21})/V$. As $V_1 > V$, and the second-period equilibrium occurs in the positive orthant of the (P_{21}, P_{22}) plane, $\lambda_1 > (V_1 + P_{21})/V > 1$. But λ_1 is a probability and a probability cannot take a value greater than 1, thereby establishing a contradiction.

The first-order condition for CSP 1 is

$$\frac{\partial \Pi_1}{\partial P_{11}} = \frac{\partial n}{\partial P_{11}} \cdot P_{11} + n + \frac{\partial n}{\partial P_{11}} \cdot [V_1 - \lambda_1 V + P_{21}] = 0.$$

CSP 1's best reply function is an implicit function, $F_1(P_{11}, P_{21}, \lambda_1)$:

$$F_1(P_{11}, P_{21}, \lambda_1) = n + \frac{\partial n}{\partial P_{11}} \cdot [P_{11} + V_1 - \lambda_1 V + P_{21}] = 0. \quad (3)$$

It follows that CPS 1's second-order condition requires $\frac{\partial^2 \Pi_1}{\partial P_{11}^2} = \frac{\partial F_1}{\partial P_{11}} < 0$.

The number of CSP 1 users is

$$n = -\frac{\partial n}{\partial P_{11}} \cdot [P_{11} + V_1 - \lambda_1 V + P_{21}]. \quad (4)$$

where $n > 0$ again requires $\frac{\partial n}{\partial P_{11}} < 0$. The number of CSP 1 users decreases in the CSP's first-period price. Furthermore, for the inequality to hold, by the characterization of n in Eq. (4):

$$\frac{\partial n}{\partial P_{11}} = -\frac{\partial n}{\partial P_{11}} - \frac{\partial^2 n}{\partial P_{11}^2} \cdot [P_{11} + V_1 - \lambda_1 V + P_{21}] \Rightarrow$$
$$\frac{\partial n}{\partial P_{11}} = -\frac{1}{2}\frac{\partial^2 n}{\partial P_{11}^2} \cdot [P_{11} + V_1 - \lambda_1 V + P_{21}],$$

which, to be negative, again requires $\frac{\partial^2 n}{\partial P_{11}^2} > 0$.

The first-period price elasticity of demand is

$$\varepsilon^n_{P_{11}} = \left| \frac{\partial n(P_{11}, P_{12})}{\partial P_{11}} \cdot \frac{P_{11}}{n(P_{11}, P_{12})} \right| = \frac{P_{11}}{P_{11} + V_1 - \lambda_1 V + P_{21}} = \frac{P_{11}}{P_{11} + P_{12}},$$

which again is inelastic. First-period price inelasticity is usually an assumption in technology adoption and switching cost models (e.g., Katz and Shapiro 1992; Klemperer 1995). Here it is instead an output of the model and, with P_{12} in the denominator, continues to reflect forward-looking users. At the same time, while the price elasticity facilitates the derivation of a firm's profit-maximizing price in one-sided markets, in two-sided platforms price derivation requires data on the price elasticity for the other side of the market as well (Arce 2020b; Tatsumoto 2021), which is beyond the scope of the present analysis. Hence, prices are characterized rather than explicitly derived. For example, $\frac{\partial \varepsilon^n_{P_{11}}}{\partial P_{21}} < 0$ implies $\frac{\partial^2 n}{\partial P_{11} \partial P_{21}} > 0$ (Vives 2018).

CSP 2's first-order condition is

$$\frac{\partial \Pi_{22}}{\partial P_{21}} = -\frac{\partial n}{\partial P_{21}} P_{21} + (N - n) - \frac{\partial n}{\partial P_{21}} [V_2 - \lambda_2 V + P_{11}] = 0.$$

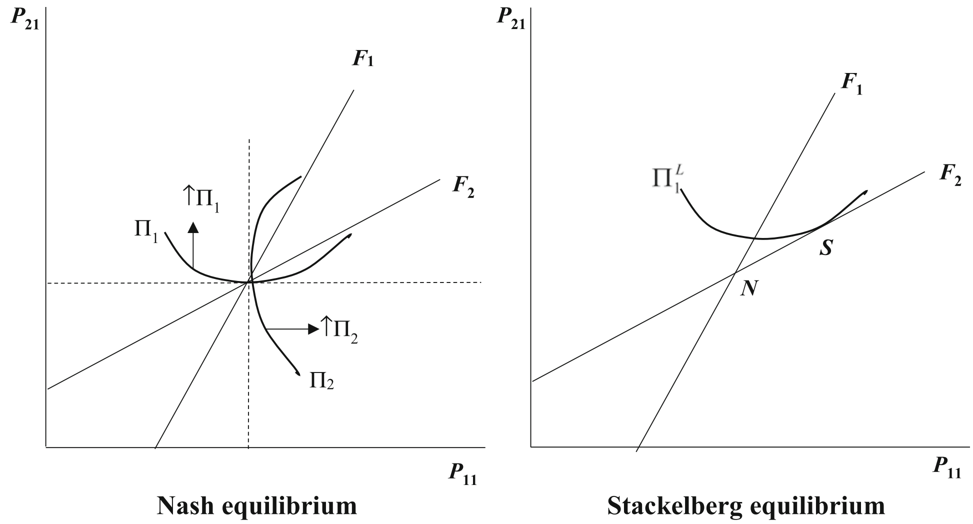


Fig. 1 Nash and Stackelberg equilibria

The following implicit function characterizes CSP 2's best reply function:

$$F_2(P_{11}, P_{21}, \lambda_2) = N - n - \frac{\partial n}{\partial P_{21}}[P_{21} + V_2 - \lambda_2 V + P_{11}] = 0. \tag{5}$$

The number of CSP 2 users is

$$N - n = \frac{\partial n}{\partial P_{21}}[P_{21} + V_2 - \lambda_2 V + P_{11}]. \tag{6}$$

An interior solution requires $N - n > 0 \Rightarrow \frac{\partial n}{\partial P_{21}} > 0$; i.e., the number of CSP 1 users increases in CSP 2's first-period price. From the user perspective the two CSPs are substitutes.

5.2 First-Period Nash Prices

The first-order conditions characterize a CSP's best reply function as an implicit function. In what follows the majority of the derivations are for CSP 1, understanding similar ones hold for CSP 2. Applying the implicit function theorem to CSP 1's best reply function, F_1, in Eq. (3):

$$\left.\frac{dP_{11}}{dP_{21}}\right|_{F_1} = -\frac{\frac{\partial F_1}{\partial P_{21}}}{\frac{\partial F_1}{\partial P_{11}}} = -\frac{\frac{\partial n}{\partial P_{21}} + \frac{\partial n}{\partial P_{11}} + \frac{\partial^2 n}{\partial P_{11}\partial P_{21}} \cdot [P_{11} + V_1 - \lambda_1 V + P_{21}]}{\frac{\partial^2 \Pi_1}{\partial P_{11}^2}}.$$

The denominator is negative by the second-order condition. Multiplying the denominator by the coefficient -1, calculating the value of $\frac{\partial n}{\partial P_{21}}$ from Eq. (4), simplifying, and signing known terms:

$$\left.\frac{dP_{11}}{dP_{21}}\right|_{F_1} = \frac{\overbrace{\frac{\partial n}{\partial P_{21}}}^{(+)}}{\underbrace{-\frac{\partial F}{\partial P_{11}}}_{(-)}} > 0.$$

When $\left.\frac{dP_{11}}{dP_{21}}\right|_{F_1} > 0$, first period prices P_{11} and P_{21} are *strategic complements*.[3] If one CSP increases (decreases) its first-period price, the other CSP's best reply is to increase (decrease) its price as well. First-period prices are also *plain complements* (Eaton and Eswaran 2002). That is, $\frac{\partial \Pi_1}{\partial P_{21}} > 0$ because $\frac{\partial n}{\partial P_{21}} > 0$; and $\frac{\partial \Pi_2}{\partial P_{11}} > 0$ because $\frac{\partial n}{\partial P_{11}} < 0$.

The left-hand panel of Fig. 1 illustrates this outcome. Best reply functions F_1 and F_2 are upward-sloping because the CSPs' first-period prices are strategic complements. The point of intersection is the Nash equilibrium. Π_1 and Π_2 are the isoprofit (level) curves for each CSP. By definition, at each point on a CSP's best reply function its isoprofit curve must be tangent to a line corresponding to the strategy of the other CSP (denoting the maximum profit, Π_i, given P_{j1}). Plain complements mean CSP 1's isoprofit curves increase in value as P_{21} increases, and CSP 2's isoprofit curves increase in value as P_{11} increases. Plain complements also mean any strategy combination in the northeast lens of Π_1 and Π_2 increases both CSPs' profits. This is where the joint-profit maximization outcome lies. Prices are higher in this event as well.

Result 2. *The CSPs' first-period prices are strategic complements. Nash prices are lower than (i) prices under perfect lock-in, and (ii) prices under joint profit maximization.*

[3] Strategic complements has nothing to do with whether users view the associated goods or services as complements (e.g., apps and CSPs) or substitutes (e.g., CSPs in a given layer of the cloud stack).

Imperfect lock-in results from user's anti-lock-in strategies. This begs the question whether CSPs can jointly raise profits by reducing price competition. A means for doing so is for one CSP to lead by committing to a price increase, as explored in the next subsection.

5.3 First-Period Stackelberg Prices

In a *Stackelberg* or *leader–follower game* the leader commits to a strategy and the follower plays its best reply to that strategy. Stackelberg games naturally arise in situations with a dominant market leader, such as AWS and IaaS. Alternatively, in an infinitely-repeated game, if a CSP is established enough be considered a long-run player, then the CSP can achieve a profit arbitrarily close to the one generated by its Stackelberg strategy provided it faces a short-run player in each period (Fudenberg and Levine 1992). Entry is a single-period event; hence, an entrant is an example of a short-run player. The interpretation of Stackelberg equilibrium that applies depends upon where a CSP lies in the cloud stack. The greater the fixed costs of entry, the less applicable is the repeated game interpretation because high entry barriers imply fewer interactions with entrants.

In a Stackelberg game with CSP 1 as the leader and CSP 2 as the follower, the leader's profit function becomes $\Pi_1(P_{11}, F_2(P_{11}, P_{21}))$, where $F_2(P_{11}, P_{21})$ is the follower's best reply function given in Eq. (5). To wit, CSP 1 maximizes its profit given the *best reply function* of CSP 2, $F_2(P_{11}, P_{21})$, whereas in a Nash equilibrium CSP 1 maximizes its profit given the *strategy* of CSP 2, P_{21}. Denoting P_{12}^f as the follower's equilibrium strategy and P_{11}^L as the leader's equilibrium strategy, the first-order conditions for the follower are

$$\frac{\partial \Pi_2}{\partial P_{21}} = F_2\left(P_{11}^L, P_{21}^f\right) = 0. \tag{7}$$

The first-order conditions for the leader are

$$\frac{\partial \Pi_1\left(P_{11}^L, F_2\left(P_{11}^L, P_{21}^f\right)\right)}{\partial P_{11}} + \frac{\partial \Pi_1\left(P_{11}^L, F_2\left(P_{11}^L, P_{21}^f\right)\right)}{\partial P_{21}} \cdot \frac{dP_{21}}{dP_{11}} = 0; \tag{8}$$

the second term captures the leader maximizing its profit given the follower's best reply to P_{11}^L.

In the right-hand panel of Fig. 1 the Stackelberg equilibrium corresponds to the leader's highest isoprofit curve given the follower's best reply. It is the point of tangency, ***S***, between Π_1^L and F_2. Given first-period prices are strategic complements, both CSPs' prices increase relative to the Nash equilibrium point, ***N***. That is, $dP_{11} > 0$, $dP_{21} > 0$. In addition, a *second-mover advantage* exists; the follower's profit increases more than the leader's because the follower can undercut the leader. Namely,

$$d\Pi_2\left(P_{11}^L, P_{21}^f\right) > d\Pi_1\left(P_{11}^L, P_{21}^f\right).$$

The total derivatives on both sides of the inequality are:

$$\frac{\partial \Pi_2\left(P_{11}^L, P_{21}^f\right)}{\partial P_{11}} dP_{11} + \frac{\partial \Pi_2\left(P_{11}^L, P_{21}^f\right)}{\partial P_{21}} dP_{21} > \frac{\partial \Pi_1\left(P_{11}^L, P_{21}^f\right)}{\partial P_{11}} dP_{11} + \frac{\partial \Pi_1\left(P_{11}^L, P_{21}^f\right)}{\partial P_{21}} dP_{21}.$$

Dividing both sides by $dP_{11} > 0$, and signing terms,

$$\underbrace{\frac{\partial \Pi_2\left(P_{11}^L, P_{21}^f\right)}{\partial P_{11}}}_{(+)} + \underbrace{\frac{\partial \Pi_2\left(P_{11}^L, P_{21}^f\right)}{\partial P_{21}}}_{(0)} \cdot \underbrace{\frac{dP_{21}}{dP_{11}}}_{(+)} > \underbrace{\frac{\partial \Pi_1\left(P_{11}^L, P_{21}^f\right)}{\partial P_{11}} + \frac{\partial \Pi_1\left(P_{11}^L, P_{21}^f\right)}{\partial P_{21}} \cdot \frac{dP_{21}}{dP_{11}}}_{(0)}.$$

The first term on the left-hand side is positive because prices are plain complements. For the second term, the first term in the product is zero because it corresponds to the follower's first-order condition in Eq. (7). Finally, the right-hand side of the inequality is zero because it corresponds to the first-order condition for the leader in Eq. (8).

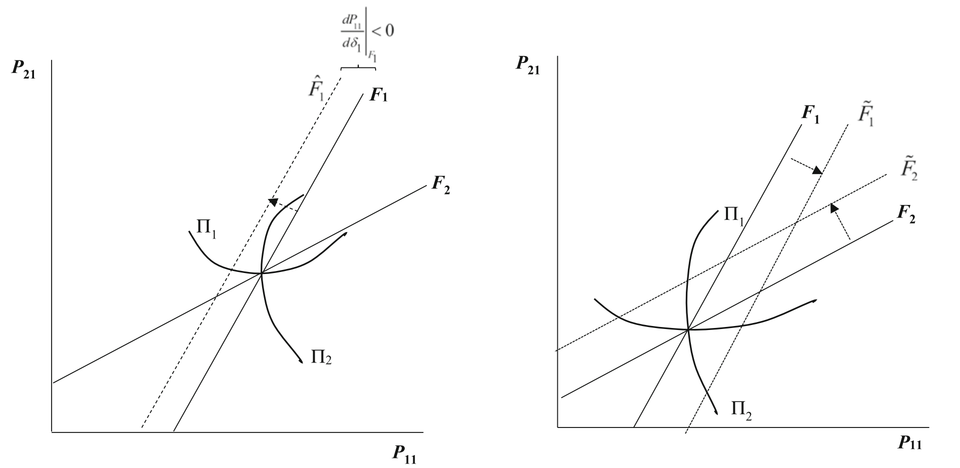
Result 3. *Both CSPs are better off if one of them acts as a first mover (in the Stackelberg sense). The first-mover (Stackelberg leader) is at a relative disadvantage because their increase in profits is less than the second-mover's (follower's). A second-mover advantage exists.*

When users engage in anti-lock-in strategies, leader–follower price competition increases CSP's profits relative to Nash competition, with the second-mover benefitting more than the first-mover. Consequently, the outcome requires CSPs to solve the coordination problem of determining who acts as leader. Alternatively, no coordination problem occurs if the CSP is a long-run concern facing potential entrants. The leader instead improves upon its Nash profit for the stage game by achieving its Stackelberg profit as a Nash equilibrium of the infinitely-repeated game.

6 First-Mover Advantage in Lock-In Leadership

In the zeroth period, users select their anti-lock-in strategies and CSPs select their security-induced lock-in strategies. The strategies affect λ_1 and/or λ_2, with users attempting to increase their values and CSPs to decrease them. From the first-order conditions in Eqs. (3) and (5),

Fig. 2 (Anti-) Lock-in effects



Unilateral ↑δ_1 by CSP 1 user

CSPs unilaterally or mutually increase lock-in (↓δ_1, ↓δ_2) increases both CSPs' profits

CSP 1's best reply function is an implicit function of λ_1, and CSP 2's is an implicit function of λ_2.

By the implicit function theorem,

$$\left.\frac{dP_{11}}{d\lambda_1}\right|_{F_1} = -\frac{\frac{\partial F_1}{\partial \lambda_1}}{\frac{\partial F_1}{\partial P_{11}}} = -\frac{\overbrace{\frac{\partial n}{\partial P_{11}}}^{(-)} V}{\underbrace{\frac{\partial^2 \Pi_1}{\partial P_{11}^2}}_{(-)\text{ by SOC}}} < 0. \tag{9}$$

By similar methods,

$$\left.\frac{dP_{21}}{d\lambda_2}\right|_{F_2} < 0. \tag{10}$$

The left-hand panel in Fig. 2 illustrates the case where a CSP 1 user increases λ_1. Given $\left.\frac{dP_{11}}{d\lambda_1}\right|_{F_1} < 0$, CSP 1's best reply function shifts to $\widehat{F}_1$. First-period prices decrease for both CSPs. The intuition is as follows. CSP 1's second-period price satisfies the no-switching constraint, making demand (the number of users) the same in both periods. At the same time, an increase in λ_1 puts downward pressure on P_{12}. CSP 1's revenue over both periods depends upon it inducing more adoptions in the first period. It does so by reducing P_{11}. In response, CSP 2 decreases P_{21} because P_{11} and P_{21} are strategic complements.

One must recognize, however, the effect on CSP 1 is only $[1/n(P_{11}, P_{21})]\cdot d\lambda_1$; i.e., there is no spillover from one user's anti-lock-in strategy affecting the degree other users are locked-in. Hence, the shift in the CSP's best reply function due to a single user's anti-lock-in strategy is much smaller than for a CSP's lock-in strategy, which affects its entire user base. Consequently, a role for government exists in reducing interoperability barriers such as security-induced lock-in. Regulation has a market-wide effect whereas individual user's anti-lock-in strategies do not. Moreover, the reduction in prices association such regulation is welfare-increasing for users, as consumer surplus is the difference between valuation and price in each period.

In the absence of regulation, when CSP 'i' increases lock-in, λ_i *decreases*. This is illustrated in the right-hand panel of Fig. 2. By the comparative statics in Eqs. (9) and (10), when both CSPs increase lock-in the new best reply functions are $\tilde{F}_1$ and $\tilde{F}_2$. At the new equilibrium both first-period prices increase. The logic is as follows. Increasing lock-in implies each CSP can raise its second-period price. Users who look ahead and reason back realize this, hence, they cannot be induced into adopting a CSP by a low price in the first period. Accordingly, both CSPs raise their first-period price.

The right-hand panel in Fig. 2 captures novel and important implications of security-induced lock-in. If either CSP unilaterally increases their degree of security-induced lock-in, $d\lambda_i < 0$, the equilibrium is in the profit-improving lens of the isoprofit curves for the Nash equilibrium. Given strategic complementarity in the first period, both CSPs benefit from either introducing or enhancing their security-induced lock-in. If CSP 1 increases P_{11} via decreasing λ_1, it additionally induces CSP 2 to increase P_{21}. Moreover, if both CSPs increase their security-induced lock-in, the new equilibrium is even further northeast in the profit-improving lens.

Finally, if CSP 1 leads by introducing or enhancing its security-induced lock-in, a first-mover advantage exists if:

$$d\Pi_1\left(\tilde{P}_{11}, \tilde{P}_{21}, \tilde{\lambda}_1\right) > d\Pi_2\left(\tilde{P}_{11}, \tilde{P}_{21}, \tilde{\lambda}_2\right).$$

Totally differentiating each profit function,

$$\frac{\partial \Pi_1}{\partial P_{11}} \cdot dP_{11} + \frac{\partial \Pi_1}{\partial P_{21}} \cdot dP_{21} + \frac{\partial \Pi_1}{\partial \lambda_1} \cdot d\lambda_1 > \frac{\partial \Pi_2}{\partial P_{11}} \cdot dP_{11} + \frac{\partial \Pi_2}{\partial P_{21}} \cdot dP_{21} + \frac{\partial \Pi_1}{\partial \lambda_2} \cdot d\lambda_2 .$$

By the first-order conditions that derive each CSP's best reply function, $\frac{\partial \Pi_1}{\partial P_{11}} = 0, \frac{\partial \Pi_2}{\partial P_{21}} = 0$. CSP 2 is passive, so $d\lambda_2 = 0$. The inequality becomes

$$\frac{\partial \Pi_1}{\partial P_{21}} \cdot dP_{21} + \frac{\partial \Pi_1}{\partial \delta_1} \cdot d\lambda_1 > \frac{\partial \Pi_2}{\partial P_{11}} \cdot dP_{11}.$$

Recognizing that $d\lambda_1 < 0 \Rightarrow dP_{11}, dP_{21} > 0$ (refer to the right-hand panel of Fig. 2), and dividing through by $d\lambda_1 < 0$ yields

$$\underbrace{\frac{\partial \Pi_1}{\partial \lambda_1}}_{\substack{(-) \\ (\partial\lambda_1 < 0 \Rightarrow \partial\Pi_1 > 0)}} < \underbrace{\frac{\partial \Pi_2}{\partial P_{11}}}_{\substack{(+) \\ (\text{plain complements})}} \times \underbrace{\frac{dP_{11}}{d\lambda_1}}_{\substack{(-) \\ (d\lambda_1 < 0 \Rightarrow dP_{11} > 0)}} - \underbrace{\frac{\partial \Pi_1}{\partial P_{21}}}_{\substack{(+) \\ (\text{plain complements})}} \times \underbrace{\frac{dP_{21}}{d\lambda_1}}_{\substack{(-) \\ (d\lambda_1 < 0 \Rightarrow dP_{21} > 0)}} .$$

Multiplying both sides by − 1,

$$\underbrace{-\frac{\partial \Pi_1}{\partial \lambda_1}}_{\substack{\text{Direct effect} \\ \text{of } \downarrow \lambda_1 \text{on} \uparrow \Pi_1,}} > \underbrace{\frac{\partial \Pi_1}{\partial P_{21}} \cdot \frac{dP_{21}}{d\lambda_1} - \frac{\partial \Pi_2}{\partial P_{11}} \cdot \frac{dP_{11}}{d\lambda_1}}_{\substack{\text{Indirect effect : differences in the CSPs'} \\ \text{profit sensitivity to their rivals' price}}} . \quad (11)$$

Increasing a CSP's degree of lock-in creates direct and indirect effects. The direct effect is it is harder for users to switch. The magnitude of the direct effect on CSP 1's profits, in absolute terms, is given in the left-hand side of Eq. (11). The indirect effect is lock-in allows both CSPs to raise first-period prices. But raising prices comes at the potential tradeoff of being undercut. This balancing act is measured on the right-hand side of Eq. (11). As prices are plain complements, both terms are positive. When the inequality is satisfied, CSPs can use security-induced lock-in to create both an increase in profits and a first-mover advantage.

Result 4. *Both CSPs' profits increase when either CSP increases their degree of security-induced lock-in (or if both do so). Moreover, under the conditions given in Eq. (11), a first-mover advantage exists. This works in favor of security-induced lock-in and against the prospects for standardization in the cloud. From the users' perspective, it highlights the importance of anti-lock-in strategies and interoperability regulation.*

The result stands in stark contrast to the second-mover advantage established for price competition. In particular, a leader's price commitment leaves an opening for price undercutting by the follower. By contrast, security-induced lock-in softens the intensity of price competition in the CSP market. Higher profits are therefore attributable to a reduction in price competition leading to a favorable outcome in an otherwise subscription-based market. When Eq. (11) is satisfied, *CSP market structure is defined by leadership on security-induced lock-in rather than undercutting one's rival*. Security figures into the characterization of CSP competition.

Equation (11) also identifies what CSP management needs to measure in order to identify when the incentives for leadership hold. Specifically, the right-hand side of the equation is expressed in terms of differences in cross-price effects on profitability, which are positive because prices are plain complements. In particular, the less sensitive a CSP's profits are to a rival's price, the more likely it gains from security-induced lock-in. If one considers Cloud 1.0 to be pay-as-you-go services allowing users to convert fixed costs into variable ones, and Cloud 2.0 as CSPs increasing their value proposition for users through increased functionality, Result 4 suggests a hastening from Cloud 1.0 to 2.0. In other words, *the increased prices stemming from security-induced lock-in need to be accompanied by CSPs increasing their value proposition for users*. For example, PaaS's are beginning to offer value-adding components such as analytics, artificial intelligence, and blockchains. Another implication for CSP market evolution is decreased cross-price effects on profitability can also be produced through vertical integration within the cloud stack. This, however, has its own potential to be anti-competitive.

7 Discussion

Information technology platforms often use security tools such as cryptography and tamper-resistance to facilitate user lock-in as part of the platform's profit strategy (Anderson 2004, 2020). For cloud services providers (CSPs), security-induced lock-in decreases CSPs' vulnerability to rivals attempting to get users to switch via price competition, and to unlicensed complementors' attempting to market compatible products. Lookabaugh and Sicker (2004) similarly observe that security-induced lock-in allows IT platforms to control potential complementors' access to users, and facilitates razor-and-blades pricing strategies for additional services and components. These studies intimate that security plays a privileged role in lock-in.

The privileged role is shown to be a consequence of security's effect on platform competition. Specifically, CSPs satisfy no-switching constraints to remain competitive within a platform environment. One way to satisfy the constraint is through security-induced lock-in. Moreover, users recognize this potentiality. Accordingly, the degree of lock-in is determined by users' anti-lock-in strategies and CSPs' security-induced lock-in strategies. In this context, CSPs increase profits by increasing their degree of lock-in. It is consistent with Opara-Martins et al. (2016) conjecture that the anticompetitive nature of the CSP market is the result of interoperability and data portability constraints stemming from CSPs' proprietary protocols. Indeed, both CSPs' profits increase when only one of the CSPs introduces or enhances security-induced lock-in. Cloud-based standards for semantics, technologies, and interfaces are therefore not in the interest of CSPs.

The situation is exacerbated when security-induced lock-in results in a first-mover advantage. This study derives previously unidentified conditions for such an advantage to exist. Specifically, a first-mover advantage in security-induced lock-in occurs when the resultant cross-price effects of the rival's prices its profits are less that the cross-price effects of its prices on its rival's profits. Consequently, the CSP competitive environment is characterized by market leaders using security and proprietary standards to limit interoperability and data portability.

These first-mover advantage conditions are also of interest to a second group of managers; namely, CSP users. The conditions fail if users' anti-lock-in strategies sufficiently diminish the first-mover's profits. Examples of anti-lock-in strategies include using a hybrid cloud; using a CSP broker; specifying the terms of exit and access to data within the service level agreement; adopting a CSP that uses standard interfaces and APIs; containerization; and adopting a CSP employing standard open security protocols. Unfortunately, CSPs have countermeasures. For example, a CSP may implement proprietary security extensions to standard security protocols. The good news for users is CSP price increases stemming from security-induced lock-in are easier to implement if they are accompanied by increases in the CSPs' value proposition for users, consistent with the cross-profit conditions for a first-mover advantage derived from the present analysis.

Moreover, the paper identifies another reason for IT management to be wary of the adverse effects of cryptography. Young and Yung (1996) predict the advent of ransomware, and this event has come to pass. One response to the threat of ransomware is for a user's CSP to cryptographically secure their data, and yet we show this can lead to data lock-in.

More generally, the paper identifies another facet of security that critically affects the nature of IT platform competition. CSPs prefer to lead in a competitive playing field characterized by (security-induced) lock-in rather than price leadership. Moreover, the current study shows that users need not be completely locked-in for CSPs to be able price as if they are. These insights provide rationales for regulation limiting interoperability and portability barriers. Specifically, regulations have an industry-wide effect whereas a user's anti-lock-in strategy has no such spillover.

A potential direction for future research is a multiperiod analysis. There are, however, several reasons why our results are likely to continue to hold. First, users are forward-looking; hence, they cannot be duped by lower prices in any single period. Second, security-induced lock-in is an intertemporal strategic complementarity. Third, the no-switching constraints must persist in order for the CSP market to remain non-monopolistic and this tempers the degree to which the first two phenomena relax price competition.

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