

Security-Induced Lock-In in the Cloud

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Abstract

Cloud services providers (CSPs) practice security-induced lock-in when employing cryptography and tamper-resistance to limit the portability and interoperability of users' data and applications. CSPs' security-induced lock-in and users' anti-lock-in strategies intersect within the context of platform competition. Given imperfect lock-in, a leader-follower pricing framework achieves a Pareto-improvement for CSPs relative to Nash equilibrium prices. This presents a coordination problem as the follower's increase in welfare exceeds that of the leader. By contrast, instituting or enhancing security-induced lock-in creates both a Pareto-improvement and first-mover advantage. CSPs therefore favor security-induced lock-in over price leadership. Consequently, standardization of semantics, technologies, and interfaces is a nonstarter for CSPs. Users' anti-lock-in strategies are discussed as a means to circumvent security-induced lock-in.

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 SMEs 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), with the complexity and integration of the relationship between the CSP and user increasing from IaaS to PaaS to SaaS.

Owing to the presence of large fixed costs stemming from substantial capacity requirements (e.g. server farms); low (effectively, zero) marginal costs from virtualization; and the commodification of services at any given layer in the stack, public CSPs have properties akin to public utilities. The analogy does not quite fit, however, as cloud 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 creates switching costs limiting their business opportunities. To wit,

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, Sahandi, and Tian 2016, pp.2, 8).

CSP lock-in stems from users' lack of portability and interoperability. *Portability* refers to the degree 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, Sokol, Liu, and Tong 2011). *Interoperability* refers to users' ability to exchange assets seamlessly across CSPs (inter-operate) (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 is the main obstacle to the achievement of portability and

interoperability” (Subramanian and Jevaraj 2019, p.38). It has implications for users’ business continuity and disaster recovery planning (Knipp, Clayton, and Watson 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. The origin of many CSPs stems 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. Consequently, no early opportunity or interest existed for anticipatory standardization at the industry level à la Bluetooth (Uotila, Keil, and Maula 2017) or a collective response to an existential threat such as creating the Extended Industry Standard for PCs as an alternative to IBM’s PS/2 Micro Channel (Canion 2013).

Anderson (2001, 2004) contends that lock-in encourages IT platforms to add security benefiting themselves rather than users. Adding security mechanisms such as cryptography and tamper-resistance controls compatibility. Lock-in creates the incentive to raise security to address a platform’s vulnerability to challengers creating compatible products, rather than address the threat of malicious outsiders or insiders. “Sometimes security solutions might be focused on other objectives than security, for instance, on achieving consumer lock-in” (Asghari, van Eeten, and Bauer 2016, p.269). Following Opara-Martins, Sahandi and Tian (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.” Lookabough and Sicker (2004) call this *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; 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 within the context of platform competition, Arce (2020) shows that cybersecurity both determines a CSP’s competitive environment (e.g. monopolistic versus imperfectly competitive) and is determined by the competitive environment. He calls this cybersecurity symbiosis. This provides context for the current analysis.

Security-induced lock-in is a form of IT investment designed to create a strategic advantage

for CSPs with respect to their users. Indeed, Guo and Ma (2018) recognize that switching costs create room for market segmentation in IT services. Alternatively, Barua, Kriebel, and Mukhopadhyay (1991) examine strategic IT investment for securing 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, lock-in investments create pricing power and data access barriers that are detrimental to users. The strategic consideration of lock-in introduces a no-switching constraint not present in Guo and Ma (2018) or Barua, Kriebel, and Mukhopadhyay (1991). Another difference is security-induced lock-in stems from cryptography and tamper-resistance. 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 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 CSP security and vulnerability to malicious threats are modeled (e.g. Gordon and Loeb 2002, Ruan 2017, and Arce 2018), 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 that lock-in is neither complete, as is usually the case in models of lock-in, nor completely absent, as is the case for users that do not adopt a CSP for fear of lock-in. CSP pricing strategies, lock-in strategies, and users' switching costs and anti-lock-in strategies are all characterized under the auspices of CSP platform competition.

The resulting game differs from prior treatments of lock-in because lock-in is security-induced and determined endogenously 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 welfare-maximizing prices for the CSPs. A Pareto-improvement is possible via leadership (in the Stackelberg sense), rather than requiring explicit or tacit cooperation. A coordination problem occurs, however, as the follower benefits more than the leader; i.e. a second-mover advantage occurs in CSP pricing. Alternatively, a Pareto-improvement and a first-mover advantage occur when CSPs increase their levels of security-induced lock-in. Consequently, standardization is a non-starter for CSPs.

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), Chen and Hitt (2006), Farrell and Klemperer (2007), and Villas-Boas (2015). Shapiro and Varian (1999) and Varian (2004) remain remarkably relevant and prescient on the intersection of lock-in, switching costs, and information technology. Lookabough and Sicker (2004) discuss four categories of security-induced lock-in: propriety security protocols; open security protocols; proprietary extensions to open security protocols; and intellectual property rights and other legal constructs.

Klemperer's (1995) switching costs categories provide a backdrop for the game-theoretic analysis of CSP platform competition to follow.

Market Power. 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 CSPs is that focusing on price allows for the user-CSP value proposition to become a little bit pregnant in the presence of price commitments. 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 that 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 being our modeling strategy.

Lock-in increases CSPs' pricing power. But users are not passive observers to the process; they act strategically to minimize its effects:

You compete at your own peril if you do not recognize lock-in and protect yourself from its adverse effects, and use it to your advantage when possible. ... The way to win in markets with switching costs is neither to avoid lock-in nor to embrace it. You need to think strategically: look ahead and reason back (Shapiro and Varian 1999, pp. 104, 111).

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.

Competitive Strategy. CSPs have the technical means to stifle competition via proprietary semantics, technologies, and interfaces. The potential for higher prices and profits implies CSPs strategically invest in switching costs, thereby making them endogenous. Anderson (2001, 2004) recasts the practice as a form of security investment that reduces an IT platform's vulnerability to switching, but diverts the platform's security away from that meant to address malicious threats. This is known as security-induced lock-in (Lookabough and Sicker 2004), and its use as a competitive strategy is our focus.

Learning Costs. CSP 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 reduces users' benefits in addition to other switching costs, such as data migration. Here, in the first period users choose between two competing CSPs with similar first-period benefits. In the second period, however, the benefits of their adopted CSP are larger due to learning effects.

Network Effects. Network effects (network externalities) occur when the benefits of using a CSP rise with the number of users of the CSP. Opara-Martins, Sahandi, and Tian (2016) find that organizations with 250+ employees realize significant benefits from increased collaboration through CSPs. Consequently, network effects can work against switching CSPs. When network effects are present, users' switching costs are endogenous. Hence, CSPs face a no-switching constraint (Lee 2014, Arce 2020). The equilibria here satisfy no-switching constraints.

3. The Model

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 no-switching constraints for users; switching costs reflecting users' learning effects with their CSP; lock-in strategies by CSPs in platform competition; and users adopting anti-lock-in strategies to keep their CSP options open. This section introduces such a model as an extensive form game.

Table 1: Notation for the Security-Induced Lock-In Game

Parameter	Description
(P_{i1}, P_{i2})	Pricing strategy for CSP ' i ' in the first and second periods, $i = 1, 2$.
N	Total number of users.
$n(P_{11}, P_{21})$	Number of users of CSP 1.
$N - n(P_{11}, P_{21})$	Number of users of CSP 2.
V	A user's first period reservation value for CSP services, $V > 0$.
$V_i \in (V, \infty)$	Reservation value for users of CSP $i = 1, 2$ in the second period.
FC_i	Fixed cost for CSP ' i .' Owing to virtualization, variable costs are negligible.
$\delta_i \in [0, 1]$	Probability that users of CSP ' i ' can access their data if switching to CSP j .

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 δ_i : its users' degree of data access if switching CSPs. Given the pair of first-period prices, (P_{11}, 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 $n(P_{11}, P_{21})$ are made: (i) $n(P_{11}, P_{21})$ is twice-differentiable over all its arguments, and (ii) if both CSP's second-period prices, P_{12} and P_{22} , satisfy no-switching constraints, then $n(P_{11}, P_{21})$ and $N - n(P_{11}, P_{21})$ carry over to the second period.

When first-period users carry over to the second period, the CSPs' 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 payoff is the sum of its first and second period revenues less its fixed costs, FC_i . Variable costs are negligible under virtualization. No discounting occurs for users or CSPs. In multi-period pricing games with switching costs, discount factors are used as a proxy for how forward-looking (price sensitive) users are to the platform strategy of enticing users with a low first-period price followed by a higher second-period price when users are locked in. Forward-looking users recognize this potentiality and are less price sensitive in the first period. Platforms recognize user's price insensitivity, consequently, first-period prices are higher when users are forward-looking. Discounting is replaced by the probability of data access, δ_i , which is an alternative forward-looking phenomenon. The difference being, in contrast to discounting, which is an exogenous preference, δ_i is co-determined by users' anti-lock-in strategies and platform competition between CSPs.

Users' select a CSP in the first period and decide whether to continue with the CSP in the second period. In addition, users partially determine their degree of data access, δ_i , when switching CSPs. Users' *anti-lock-in strategies* include keeping proprietary data in-house, resulting in a hybrid cloud; using a CSP broker; or contractually obligating their CSP to provide the data in an agreed upon format upon exit. Opting for a CSP with standard interfaces and APIs or one employing standard open security protocols are also possibilities. Another tactic is spreading data over multiple CSPs, perhaps by using erasure coding (Razavian et al 2013), as a user version of defense-in-depth (Anderson 2001). Such strategies increase δ_i .

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' impetus for adopting a CSP is to transform fixed IT capital expenses into pay-as-you-go variable operating costs. Such savings are initially the same irrespective of the CSP adopted.

A user continuing with their CSP in the second period receives net benefit $V_i - P_{i2}$, where $V_i \in (V, \infty)$. Specifying $V_i > V$ is consistent with accruing learning effects when continuing with a CSP. A subtle but important point is that a user who switches CSPs in period 2 accrues benefit V because no learning effect carries over. Switching users also pay the lower first-period price charged by their newly adopted CSP, P_{j1} . In other words,

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

The result is a dynamic not commonly present in models of lock-in. The dynamic captures users' learning effect when continuing with a CSP, an *advantage* of lock-in.

The timing of the game reflects the above description. The game consists of three stages. 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 adding an initial ('zeroth') period for determining the degree of lock-in. A major difference between the present analysis and other analyses of endogenous switching costs is that 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) switching

constraints incorporate learning effects. Finally, in allowing for Shapiro and Varian's (1999) principle that, the potential for lock-in necessitates that participants look ahead and reason back, the solution concept used is subgame perfect Nash equilibrium (SPNE).

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

In the benchmark situation users are locked into their CSP in the second period. Compared to the general game, $\bar{\delta}_i = 0$, $i = 1, 2$. No zeroth period occurs. Variables in this section have an overbar to distinguish them from the general case.

Solving the game by SPNE means that 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 revenue subject to a participation constraint for its users. For CSP 1:

$$\max_{\bar{P}_{12}} n(\bar{P}_{11}, \bar{P}_{21}) \cdot \bar{P}_{12} \quad s.t. \quad \underbrace{\bar{P}_{12} \leq V_1}_{\text{users' participation constraint}}.$$

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

In the first period CSP 1 selects \bar{P}_{11} to maximize $\Pi_1 = \Pi_{11} + \Pi_{12}$:

$$\max_{\bar{P}_{11}} n(\bar{P}_{11}, \bar{P}_{21}) \cdot \bar{P}_{11} + n(\bar{P}_{11}, \bar{P}_{21}) \cdot \bar{P}_{12} - FC_1 = \max_{\bar{P}_{11}} n(\bar{P}_{11}, \bar{P}_{21}) \cdot \bar{P}_{11} + n(\bar{P}_{11}, \bar{P}_{21}) \cdot V_1 - FC_1$$

Suppressing the arguments in $n(\bar{P}_{11}, \bar{P}_{21})$, CSP 1's first order condition is:

$$(1) \quad \frac{\partial \Pi_1}{\partial \bar{P}_{11}} = \frac{\partial n}{\partial \bar{P}_{11}} \cdot \bar{P}_{11} + n + \frac{\partial n}{\partial \bar{P}_{11}} \cdot V_1 = 0 \Rightarrow n = -\frac{\partial n}{\partial \bar{P}_{11}} \cdot (\bar{P}_{11} + V_1).$$

For this to make sense ($n > 0$) requires $\frac{\partial n}{\partial \bar{P}_{11}} < 0$; i.e. the number of users satisfies the law of

demand. From the characterization of n given by Eq. (1):

$$(2) \quad \frac{\partial n}{\partial \bar{P}_{11}} = -\frac{\partial n}{\partial \bar{P}_{11}} - \frac{\partial^2 n}{\partial \bar{P}_{11}^2} \cdot (\bar{P}_{11} + V_1) \Rightarrow \frac{\partial n}{\partial \bar{P}_{11}} = -\frac{1}{2} \cdot \frac{\partial^2 n}{\partial \bar{P}_{11}^2} \cdot (\bar{P}_{11} + V_1).$$

It follows that $\frac{\partial n}{\partial \bar{P}_{11}} < 0$ requires $\frac{\partial^2 n}{\partial \bar{P}_{11}^2} > 0$. User demand is convex. Furthermore, a user's

first-period elasticity of demand is:

$$\varepsilon_{\bar{P}_{11}}^n = \left| \frac{\partial n}{\partial \bar{P}_{11}} \cdot \frac{\bar{P}_{11}}{n(\bar{P}_{11}, \bar{P}_{21})} \right| = \frac{\bar{P}_{11}}{(\bar{P}_{11} + V_1)}.$$

A user's first-period price elasticity is inelastic ($\varepsilon_{P_1}^n < 1$). Price insensitivity is due to users looking ahead and reasoning back, keeping them from being duped by 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:

$$\Pi_i = n(P_i, P_j)P_i + n(P_i, P_j)V - FC_i = 0 \Rightarrow P_i = \frac{FC_i}{n(P_i, P_j)} - V.$$

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 $\delta_i \in (0,1)$ 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. The no-switching constraint accounts for the probability, δ_i , of a user accessing its data to switch CSPs. In addition, the no-switching constraint supersedes the need for a participation constraint for users. CSP 1's pricing problem becomes:

$$\max_{P_{12}} n(P_{11}, P_{21}) \cdot P_{12} \quad s.t. \underbrace{\delta_1 (V - P_{21})}_{\text{no-switching constraint}} \leq V_1 - P_{12}.$$

If CSP 1 users switch to CSP 2 the associated benefit is V and not V_2 because no learning effect occurs for the new CSP. Moreover, users pay P_{21} rather than P_{22} because they are in their first period with CSP 2. Satisfying the no-switching constraint implies that $n(P_{11}, P_{21})$ carries over to period 2. Solving the no-switching constraint for P_{12} yields:

$$P_{12} \leq V_1 - \delta_1 (V - P_{21}).$$

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

$$P_{22} \leq V_2 - \delta_2 (V - P_{11}).$$

When $\delta_1, \delta_2 = 0$, the benchmark condition, $P_{i2} = V_i$, is satisfied. Otherwise, second-period prices are lower under imperfect lock-in, $\delta_1, \delta_2 \in (0,1)$.

5.1 First-Period Best Replies

The two-period profit functions for each CSP are:

$$\begin{aligned}\Pi_1 &= n(P_{11}, P_{21}) \cdot P_{11} + n(P_{11}, P_{21}) \cdot P_{12} - FC_1 \\ \Pi_2 &= (N - n(P_{11}, P_{21}))P_{21} + (N - n(P_{11}, P_{21}))P_{22} - FC_2\end{aligned}$$

Substituting in the solutions for second-period prices, P_{12} and P_{22} :

$$\begin{aligned}\Pi_1 &= n(P_{11}, P_{21}) \cdot P_{11} + n(P_{11}, P_{21}) \cdot [V_1 - \delta_1(V - P_{21})] - FC_1 \\ \Pi_2 &= (N - n(P_{11}, P_{21}))P_{21} + (N - n(P_{11}, P_{21})) [V_2 - \delta_2(V - P_{11})] - FC_2\end{aligned}$$

The first-order condition for CSP 1 is:

$$\frac{\partial \Pi_1}{\partial P_{11}} = \frac{\partial n}{\partial P_{11}} \cdot P_{11} + n + \frac{\partial n}{\partial P_{11}} \cdot [V_1 - \delta_1(V - P_{21})] = 0.$$

CSP 1's best reply function is an implicit function, $F_1(P_{11}, P_{21}, \delta_1)$:

$$(3) \quad F_1(P_{11}, P_{21}, \delta_1) = n + \frac{\partial n}{\partial P_{11}} \cdot [P_{11} + V_1 - \delta_1(V - P_{21})] = 0$$

The number of CSP 1 users is:

$$(4) \quad n = -\frac{\partial n}{\partial P_{11}} \cdot [P_{11} + V_1 - \delta_1(V - P_{21})]$$

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):

$$\frac{\partial n}{\partial P_{11}} = -\frac{\partial n}{\partial P_{11}} - \frac{\partial^2 n}{\partial P_{11}^2} \cdot [P_{11} + V_1 - \delta_1(V - P_{21})] \Rightarrow \frac{\partial n}{\partial P_{11}} = -\frac{1}{2} \frac{\partial^2 n}{\partial P_{11}^2} \cdot [P_{11} + V_1 - \delta_1(V - P_{21})],$$

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

CSP 2's first-order condition is:

$$\frac{\partial \Pi_2}{\partial P_{21}} = -\frac{\partial n}{\partial P_{21}} P_{21} + (N - n) - \frac{\partial n}{\partial P_{21}} [V_2 - \delta_2(V - P_{11})] = 0.$$

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

$$(5) \quad F_2(P_{11}, P_{21}, \delta_2) = N - n - \frac{\partial n}{\partial P_{21}} [P_{21} + V_2 - \delta_2(V - P_{11})] = 0.$$

The number of CSP 2 users is:

$$(6) \quad N - n = -\frac{\partial n}{\partial P_{21}} [P_{21} + V_2 - \delta_2(V - P_{11})].$$

Where $N - n > 0 \Rightarrow \frac{\partial n}{\partial P_{21}} > 0$; i.e. the number of CSP 1 users increases in CSP 2's first-period price.

The two CSPs are substitutes. For the inequality to hold, by the characterization of n in Eq. (4):

$$\frac{\partial n}{\partial P_{21}} = \underbrace{-\delta_1}_{(+)} \underbrace{\frac{\partial n}{\partial P_{11}}}_{(-)} - \underbrace{\frac{\partial^2 n}{\partial P_{11} \partial P_{21}}}_{(?)} \cdot \underbrace{[P_{11} + V_1 - \delta_1 (V - P_{21})]}_{(+)} > 0.$$

In order to sign $\frac{\partial^2 n}{\partial P_{11} \partial P_{21}}$, first recognize that $\frac{\partial^2 n}{\partial P_{11} \partial P_{21}} = \frac{\partial^2 n}{\partial P_{21} \partial P_{11}}$. From Eq. (4), $\frac{\partial n}{\partial P_{21}} = -\delta_1 \cdot \frac{\partial n}{\partial P_{11}}$.

This implies $\frac{\partial^2 n}{\partial P_{21} \partial P_{11}} = \underbrace{-\delta_1}_{(-)} \cdot \underbrace{\frac{\partial^2 n}{\partial P_{11}^2}}_{(+)} = \frac{\partial^2 n}{\partial P_{11} \partial P_{21}} < 0$. Hence, $\frac{\partial n}{\partial P_{21}} > 0$.

Finally, a user's first-period price elasticity is:

$$\varepsilon_{P_{11}}^n = \left| \frac{\partial n(P_{11}, P_{12})}{\partial P_{11}} \cdot \frac{P_{11}}{n(P_{11}, P_{12})} \right| = \frac{P_{11}}{[P_{11} + V_1 - \delta_1 (V - P_{21})]},$$

which again is inelastic. First-period inelasticity at the user level is usually an assumption in technology adoption and switching cost models (e.g. Katz and Shapiro 1992, Klemperer 1995). Here it is an output of the model.

5.2 First-Period Nash Prices

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

$$\left. \frac{dP_{11}}{dP_{21}} \right|_{F_1} = - \frac{\frac{\partial F_1}{\partial P_{21}}}{\frac{\partial F_1}{\partial P_{11}}} = - \frac{\frac{\partial n}{\partial P_{21}} - \delta_1 \frac{\partial n}{\partial P_{11}} - \frac{\partial^2 n}{\partial P_{11} \partial P_{21}} \cdot [P_{11} + V_1 - \delta_1 (V - P_{21})]}{\frac{\partial n}{\partial P_{11}} - \frac{\partial n}{\partial P_{11}} - \frac{\partial^2 n}{\partial P_{11}^2} [P_{11} + V_1 - \delta_1 (V - P_{21})]}.$$

Simplifying, multiplying the denominator by the coefficient -1, and signing known terms:

¹ Stability of the equilibrium – in the Nash/best reply sense – requires that the slope of CSP 1's best reply function exceeds that of CSP 2's best reply function. The left-hand panel of Figure 1 illustrates this. If CSP 1's price is \hat{P}_{11} , the resulting sequence of best replies, shown by the arrows, leads to the Nash equilibrium. Related to this, the second-order conditions are given in the appendix.

$$\left. \frac{dP_{11}}{dP_{21}} \right|_{F_1} = \frac{\overbrace{\frac{\partial n}{\partial P_{21}}}^{(+)} - \delta_1 \overbrace{\frac{\partial n}{\partial P_{11}}}^{(-)} - \overbrace{\frac{\partial^2 n}{\partial P_{11} \partial P_{21}}}^{(-)} \cdot \overbrace{[P_{11} + V_1 - \delta_1 (V - P_{21})]}^{(+)}}{\underbrace{\frac{\partial^2 n}{\partial P_{11}^2}}_{(+)} \underbrace{[P_{11} + V_1 - \delta_1 (V - P_{21})]}_{(+)}} > 0.$$

When $\left. \frac{dP_{11}}{dP_{21}} \right|_{F_1} > 0$, first period prices P_{11} and P_{21} are *strategic complements*. If one CSP increases (decreases) its first-period price the other CSP's best reply is to increase (decrease) its price as well.² First-period prices are also *plain complements* (Eaton and Eswaran 2002). That is,

$$\frac{\partial \Pi_1}{\partial P_{21}} > 0 \text{ because } \frac{\partial n}{\partial P_{21}} > 0; \text{ and } \frac{\partial \Pi_2}{\partial P_{11}} > 0 \text{ because } \frac{\partial n}{\partial P_{11}} < 0.$$

The left-hand panel of Figure 1 illustrates this outcome. Best reply functions F_1 and F_2 are upward sloping because the CSP's first-period prices are strategic complements. The point of intersection is the Nash equilibrium. Π_1 and Π_2 are the isopayoff (level) curves for each CSP. By definition, at each point on a CSP's best reply function its isopayoff curve must be tangent to a line corresponding to the strategy of the other player (denoting the maximum payoff, Π_i , given P_{j1}). Plain complements mean that CSP 1's isopayoff curves increase in value as P_{21} increases and CSP 2's isopayoff curves increase in value as P_{11} increases. Any strategy combination in the northeast lens of Π_1 and Π_2 is a Pareto-improvement. Both prices are higher in this event.

Result 1. *The CSP's first-period prices are strategic complements. Nash prices are lower than (i) the prices under perfect lock-in, and (ii) the Pareto-efficient prices under CSP cooperation.*

This begs the question whether CSPs can achieve a Pareto-improvement.

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, with a commensurately large discount

² Strategic complements has nothing to do with whether users view the associated goods as complements (e.g. apps and CSPs) or substitutes (e.g. CSPs in a given layer of the cloud stack).

factor, then the CSP can achieve a payoff arbitrarily close to the one generated by its Stackelberg strategy, provided it faces a short-run player in each period (Fudenberg and Levine 1992). An entrant is an example of a short-run player. Entry is a single-period event; hence, at any point in time the entrant for that period plays what they consider their best reply to the long-run player's strategy. This justifies a potential costly investment in reputation in terms of a transitory payoff for the Stackelberg strategy against a short-run player's strategy that may not be a best reply to the Stackelberg strategy. Ultimately, investing in the reputation of the Stackelberg strategy causes short-run players to play their best reply to the Stackelberg strategy. By this process, the Stackelberg outcome for the stage game becomes a Nash equilibrium payoff for the infinitely-repeated game. 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, CSP 2's payoff remains $\Pi_2(P_{11}, P_{21})$. By contrast, the leader's payoff 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). In a Stackelberg equilibrium CSP 1 maximizes its payoff given the *best reply function* of CSP 2, $F_2(P_{11}, P_{21})$, whereas in a Nash equilibrium CSP 1 maximizes its payoff 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

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

The first-order conditions for the leader are

$$(8) \quad \frac{\partial \Pi_1(P_{11}^L, P_{21}^f)}{\partial P_{11}} + \frac{\partial \Pi_1(P_{11}^L, P_{21}^f)}{\partial P_{21}} \cdot \frac{dP_{21}^f}{dP_{11}} = 0,$$

where the second term captures the leader maximizing its payoff given that the follower plays its best reply to P_{11}^L .

In the right-hand panel of Figure 1 the Stackelberg equilibrium corresponds to the leader's highest isopayoff curve given the follower's best reply. It is the point of tangency, S , between Π_1^L and F_2 . Given that first-period prices are strategic complements, both CSP's prices increase

relative to the Nash equilibrium point, N . That is, $dP_{11} > 0$ and $dP_{21} > 0$. Furthermore, when additionally recognizing that first-period prices are pure complements, a *second-mover advantage* exist such that the follower's payoff increases more than the leader's:

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

To see this, apply the definition of total derivative to both sides of the inequality:

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

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

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

The first term on the left-hand side is positive because prices are pure 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 2. *Both CSPs are better off if one of them acts as a first mover (in the Stackelberg sense). Neither explicit nor tacit cooperation is necessary for a Pareto-improvement. The first-mover (Stackelberg leader) is at a disadvantage because their increase in payoff is less than the second-mover's (follower's). A second-mover advantage exists.*

A Pareto-improvement 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 payoff for the stage game by achieving its Stackelberg payoff as a Nash equilibrium of the infinitely-repeated game.

6. CSPs Favors Security-Induced Lock-In Over Price

In the zeroth period, users select their anti-lock-in strategies and CSPs select their security-induced lock-in strategies. The strategies affect δ_1 and/or δ_2 , with users attempting to increase their values and CSPs to decrease them. From the first-order conditions in Eqs. (3) and (5), CSP 1's best reply function is an implicit function of δ_1 and CSP 2's is an implicit function of δ_2 .

By the implicit function theorem:

$$\left. \frac{dP_{11}}{d\delta_1} \right|_{F_1} = - \frac{\frac{\partial F_1}{\partial \delta_1}}{\frac{\partial F_1}{\partial P_{11}}} = - \frac{\frac{\partial n}{\partial P_{11}}(V - P_{21})}{\frac{\partial n}{\partial P_{11}} - \frac{\partial n}{\partial P_{11}} - \frac{\partial^2 n}{\partial P_{11}^2} [P_{11} + V_1 - \delta_1(V - P_{21})]}.$$

Simplifying, multiplying the denominator by the coefficient -1, and signing known terms:

$$(9) \quad \left. \frac{dP_{11}}{d\delta_1} \right|_{F_1} = \frac{\overbrace{\frac{\partial n}{\partial P_{11}}(V - P_{21})}^{(-) \geq 0}}{\underbrace{\frac{\partial^2 n}{\partial P_{11}^2} [P_{11} + V_1 - \delta_1(V - P_{21})]}_{(+)}} < 0.$$

By similar methods,

$$(10) \quad \left. \frac{dP_{21}}{d\delta_2} \right|_{F_2} < 0.$$

The left-hand panel in Figure 2 illustrates the case where a CSP 1 user increases δ_1 . Given

$\left. \frac{dP_{11}}{d\delta_1} \right|_{F_1} < 0$, CSP 1's best reply function shifts to \hat{F}_1 . One must recognize, however, that without

coordination among CSP 1 users, the effect on CSP 1 is only $[1/n(P_1, P_2)] \cdot d\delta_1$; i.e. the shift is much smaller for a single user's anti-lock-in strategy than it is for a CSP's lock-in strategy, which affects its entire user base. At the new equilibrium the 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 δ_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.

Turning to the right-hand panel in Figure 2, when CSP 'i' increases lock-in δ_i decreases. 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 that each CSP can raise its second-period price. Users who look ahead and reason back realize this, hence, they cannot be duped 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 Figure 2 captures novel and important implications of security-induced lock-in. If either CSP unilaterally increases their degree of security-induced lock-in, $d\delta_i < 0$, the equilibrium is in the Pareto-improvement lens of the isopayoff 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 δ_1 , it additionally induces CSP 2 to increase P_{21} and vice-versa. No such interdependence exists between CSP users. Moreover, if both CSPs increase their security-induced lock-in the new equilibrium is even further northeast in the Pareto-improvement lens.

Finally, if CSP 1 leads by introducing or enhancing its security-induced lock-in, no coordination problem occurs if

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

Totally differentiating each payoff function:

$$\frac{\partial \Pi_1}{\partial P_{11}} \cdot dP_{11} + \frac{\partial \Pi_1}{\partial P_{21}} \cdot dP_{21} + \frac{\partial \Pi_1}{\partial \delta_1} \cdot d\delta_1 > \frac{\partial \Pi_2}{\partial P_{11}} \cdot dP_{11} + \frac{\partial \Pi_2}{\partial P_{21}} \cdot dP_{21} + \frac{\partial \Pi_2}{\partial \delta_2} \cdot d\delta_2$$

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 $d\delta_2 = 0$. The inequality becomes

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

Recognizing that $d\delta_1 < 0 \Rightarrow dP_{11}, dP_{21} > 0$ (refer to the right-hand panel of Figure 2), and dividing through by $d\delta_1 < 0$, yields:

$$\underbrace{\frac{\partial \Pi_1}{\partial \delta_1}}_{\substack{(-) \\ (\partial \delta_1 < 0 \Rightarrow \partial \Pi_1 > 0)}} < \underbrace{\frac{\partial \Pi_2}{\partial P_{11}}}_{\substack{(+)} \text{ (pure complements)}} \times \underbrace{\frac{dP_{11}}{d\delta_1}}_{\substack{(-)} \text{ (} d\delta_1 < 0 \Rightarrow dP_{11} > 0 \text{)}} - \underbrace{\frac{\partial \Pi_1}{\partial P_{21}}}_{\substack{(+)} \text{ (pure complements)}} \times \underbrace{\frac{dP_{21}}{d\delta_1}}_{\substack{(-)} \text{ (} d\delta_1 < 0 \Rightarrow dP_{21} > 0 \text{)}}.$$

Multiplying both sides by -1:

$$(11) \quad \underbrace{-\frac{\partial \Pi_1}{\partial \delta_1}}_{\substack{\text{Direct effect} \\ \text{of } \delta_1 \text{ on } \Pi_1,}} > \underbrace{\frac{\partial \Pi_1}{\partial P_{21}} \cdot \frac{dP_{21}}{d\delta_1}}_{\substack{\text{Indirect effect} \\ \text{of } P_{21} \text{ on } \Pi_1}} - \underbrace{\frac{\partial \Pi_2}{\partial P_{11}} \cdot \frac{dP_{11}}{d\delta_1}}_{\substack{\text{Indirect effect} \\ \text{of } P_{11} \text{ on } \Pi_2}}.$$

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 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, with the increase in the rival's price adding to a CSP's profits because, from the user's perspective, in the first period the CSPs are substitutes. The right-hand side of Eq. (11) is the difference between the indirect effect on CSP 1's profits and that for CSP 2. When the inequality is satisfied, no coordination problem arises to inhibit a CSP's use of security-induced lock-in to effect a Pareto improvement.

Result 3. *It is Pareto-improving for either CSP (or both CSPs) to increase their degree of security-induced lock-in. Moreover, under the conditions given in Eq. (11), a first-mover advantage exists. That is, no formal or tacit cooperation mechanism is needed to implement a Pareto-improvement nor need a coordination problem arise (contrary to the case of Stackelberg pricing). 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.*

CSPs need not resort to price leadership and its attenuate coordination problem to achieve a Pareto-improvement. An incentive instead exists in the form of a first-mover advantage with respect to security-induced lock-in that achieves a Pareto improvement for the CSPs. CSP market structure is thus defined by leadership on security-induced lock-in rather than price leadership.

7. Discussion

Information technology platforms often divert security efforts intended to bolster their platform against malicious threats in favor of efforts toward lock-in-via-security as part of the platform's profit strategy (Anderson 2001, 2004). For cloud services providers (CSPs) security-induced lock-in decreases the CSPs' vulnerability to challengers attempting to get users to switch and unlicensed complementors' attempting to market compatible products. Lookabough 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. Both studies intimate that security plays a privileged role in lock-in.

The privileged role is shown to be a consequence of security-induced lock-in's effect on CSPs' pricing strategies, particularly since prices are strategic complements. Specifically, CSPs face no-switching constraints when choosing their pricing strategies. One way to satisfy the constraint is through security-induced lock-in. Moreover, users recognize this potentiality. Accordingly, the degree of lock-in is endogenously determined by users' anti-lock-in strategies

and CSPs' security-induced lock-in strategies. In this context, it is Pareto-improving for CSPs to increase their degree of lock-in. This is consistent with Opara-Martins, Sahandi, and Tian's (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, a Pareto-improvement occurs 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.

Moreover, combining users' anti-lock-in strategies with CSPs' no-switching constraints yields the conditions for security-induced lock-in creating a first-mover advantage. The conditions fail if the effect of the first-mover's price on the second-mover's profits exceeds that of the second-mover's price on the first-mover's profits. As a second-mover advantage exists in setting price, this is unlikely to be the case.

The conditions also 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 or spreading organizationally critical data across CSPs; 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; 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. Or using a broker can result in lock-in with the broker. Overall, it is unlikely that users' anti-lock-in strategies can violate the conditions for a first-mover advantage from security-induced lock-in because, whilst CSPs influence lock-in across their user base, a user only affects their own degree of lock-in.

CSP price leadership produces a Pareto improvement but concedes a second-mover advantage. By contrast, security-induced lock-in produces both a Pareto improvement and a first-mover advantage. This provides a clear rationale for security-induced lock-in. In CSP markets, however, security-induced lock-in versus malicious threat security is not an easy tradeoff for at least two reasons. First, insecurity against malicious threats is a primary motive for switching CSPs (Wilms, Stieglitz, and Müller 2018). Second, Arce (2020) demonstrates that security against malicious threats is the defining factor determining whether the user side of platform markets are winner-take-all or imperfectly competitive. A comprehensive understanding of CSPs, users, and market structure ultimately entails combining security-induced lock-in and cybersecurity within a single model.

Appendix: Second-Order Conditions for the General Model

Given implicit best reply function $F_1(P_{11}, P_{21}, \delta_1)$ for CSP 1, and implicit best reply function,

$F_2(P_{11}, P_{21}, \delta_2)$, for CSP 2, define the following:

$$\frac{\partial^2 \Pi_{11}}{\partial P_{11}^2} = \frac{\partial F_1(P_{11}, P_{21}, \delta_1)}{\partial P_{11}} = F_{11}; \quad \frac{\partial^2 \Pi_{11}}{\partial P_{11} \partial P_{21}} = \frac{\partial F_1(P_{11}, P_{21}, \delta_1)}{\partial P_{21}} = F_{12}$$

$$\frac{\partial^2 \Pi_{21}}{\partial P_{21}^2} = \frac{\partial F_2(P_{11}, P_{21}, \delta_2)}{\partial P_{21}} = F_{22}; \quad \frac{\partial^2 \Pi_{21}}{\partial P_2 \partial P_1} = \frac{\partial F_2(P_{11}, P_{21}, \delta_1)}{\partial P_1} = F_{21}$$

In contrast to the notation up until this point, where the first subscript denotes the CSP and the second subscript the time period, here the notation has changed. Specifically, F_{ik} denotes the partial derivative of the first period best response function of CSP ‘ i ’ (F_i) with respect to the first period price of CSP ‘ k ’ (P_{k1}): $F_{ik} = \partial F_i / \partial P_{k1}$.

It follows that the second-order conditions for a Nash equilibrium require

$$F_{11} < 0, F_{22} < 0.$$

Moreover, given upward-sloping best reply functions, the equilibrium is stable – in the Nash/best reply sense – if the slope of CSP 1’s best reply function exceeds that of 2’s best reply function:

$$\frac{dP_{11}}{dP_{21}} = -\frac{F_{12}}{F_{11}} > -\frac{F_{22}}{F_{21}} = \frac{dP_{21}}{dP_{11}} \Rightarrow F_{11}F_{22} - F_{12}F_{21} > 0.$$

Finally, strategic complements implies $\frac{dP_{11}}{dP_{21}} \Big|_{F_1} = -\frac{F_{12}}{\underbrace{F_{11}}_{(-)}} > 0 \Rightarrow F_{12} > 0$. Similarly,

$$\frac{dP_{11}}{dP_{21}} \Big|_{F_2} = -\frac{F_{21}}{\underbrace{F_{22}}_{(-)}} > 0 \Rightarrow F_{21} > 0.$$

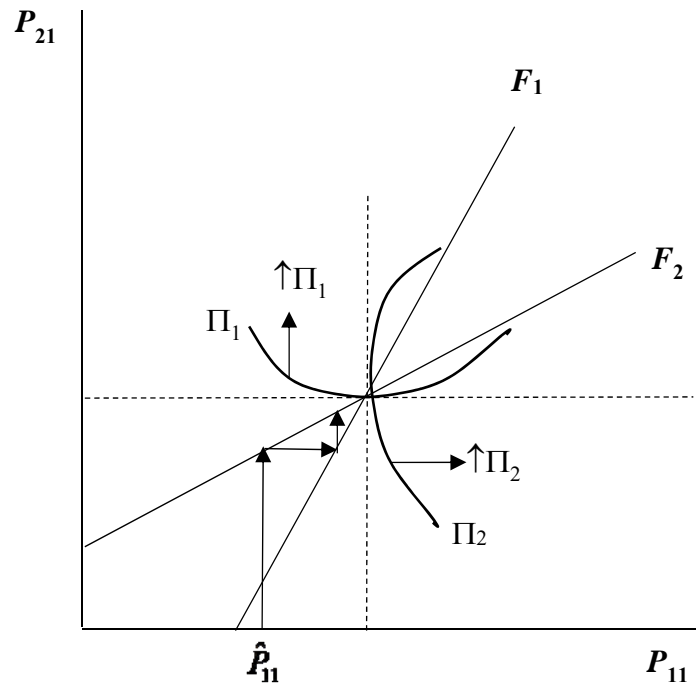
References

- Anderson, Ross J. 2001. *Security Engineering*. Indianapolis, IN: Wiley.
- Anderson, Ross J. 2004. Cryptography and Competition Policy – Issues with ‘Trusted Computing.’ In L.J. Camp and S. Lewis (eds) *Economics of Information Security*. Norwell, MA: Kluwer Academic, pp. 35-52.
- Arce, Daniel G. 2018. Malware and Market Share. *Journal of Cybersecurity* 4(1) 1-6.
- Arce, Daniel G. 2020. Cybersecurity and Platform Competition in the Cloud. *Computers & Security*, 93: 1-9.
- Asghari, Hadi, Michel van Eeten, and Johannes M. Bauer 2016. Economics of Cybersecurity. In Johannes M. Bauer and Michael Latzer, *Handbook on the Economics of the Internet*. Northampton, MA: Elgar, pp. 262-287.
- Barua, Anitesh, Charles H. Kriebel, and Tridas Mukhopadhyay 1991. An Economic Analysis of Strategic Information Technology Investments. *MIS Quarterly* 15(3) 313-331.
- Burns, Matthew 2012. Cloud-Based ERP: The Risk of Vendor Lock-In. *Emerging Issues and Technologies for ERP Systems*, pp.77-80.
- Canion, Rod 2013. *Open*. Dallas: Benbella Books.
- Chen, Pei-yu and Lorin M. Hitt 2006. Information Technology and Switching Costs. In T. Hendershott (ed.) *Economics and Information Systems*, Volume 1. Bingley, UK: Emerald, pp.437-470.
- Eaton, B. Curtis and Mukesh Eswaran 2002. Noncooperative Equilibria in 1-Shot Games: A Synthesis. In B. Curtis Eaton, *Applied Microeconomic Theory*. Northampton, MA: Edward Elgar, pp. 118-149.
- Farrell, Joseph and Paul Klemperer. 2007 Coordination and Lock-In: Competition with Switching Costs and Network Effects. In M. Armstrong and R. Porter (eds), *Handbook of Industrial Organization*, Volume 3, Amsterdam: Elsevier, pp.1967-2072.
- Fudenberg, Drew and David K. Levine 1992. Maintaining a Reputation when Strategies are Imperfectly Observed. *Review of Economic Studies* 59(3) 561-579.
- Gordon, Lawrence A. and Martin P. Loeb 2002. The Economics of Information Security Investment. *ACM Transactions on Information and System Security* 5(4) 438-457.
- Guo, Zhiling and Dan Ma 2018. A Model of Competition between Perpetual Software and Software as a Service. *MIS Quarterly* 42(1) 101-120.

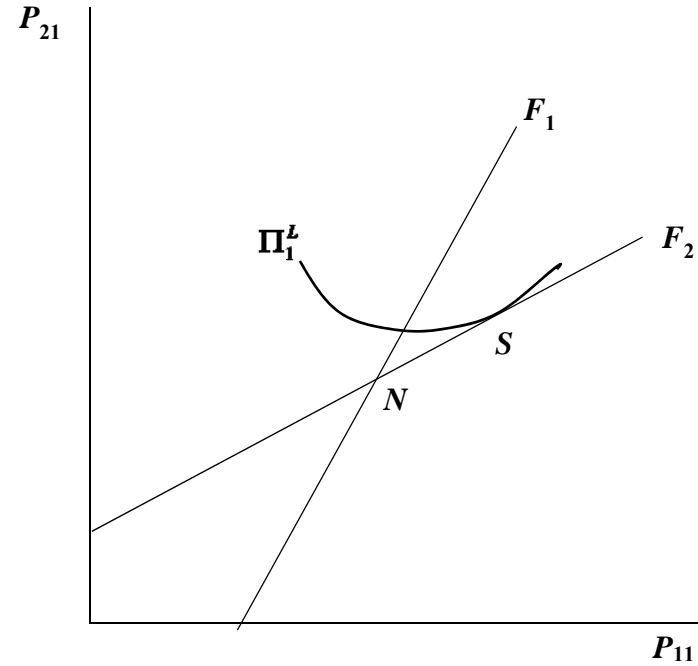
- Hogan, Michael, Annie Sokol, Fang. Liu, and Jin Tong 2011. *NIST Cloud Computing Standards Roadmap*. Gaithersburg, MD: National Institute of Standards and Technology Special Publication 500-291.
- Katz, Michael L. and Carl Shapiro 1992. Production Introduction with Network Externalities. *Journal of Industrial Economics* 40(1) 55-83.
- Klemperer, Paul 1995. Competition when Consumers Have Switching Costs: An Overview with Applications to Industrial Organization, Macroeconomics, and International Trade. *Review of Economic Studies* 62(4) 515-539.
- Knipp, Eric, Traverse Clayton, and Richard Watson 2016. *A Guidance Framework for Architecting Portable Cloud and Multicloud Applications*. Stamford, CT: Gartner.
- Lee, Robin 2014. Competing Platforms. *Journal of Economics & Management Strategy* 23(3) 507-526.
- Lookabaugh, Tom and Douglas C. Sicker 2004. Security and Lock-In. In L.J. Camp and S. Lewis (eds) *Economics of Information Security*. Norwell, MA: Kluwer Academic, pp. 225-246.
- Opara-Martins, Justice, Reza Sahandi, and Feng Tian 2016. Critical Analysis of Vendor Lock-In and Its Impact on Cloud Computing Migration: A Business Perspective. *Journal of Cloud Computing: Advances, Systems and Applications* 5(4) 1-18.
- Padilla, A.J. 1991. Consumer Switching Costs: A Survey. *Investicacions Económicas* (Segunda época) 15(3) 485-504.
- Pectu, Dana. 2011. Portability and Interoperability between Clouds: Challenges and Case Study. In: W. Abramowicz et al (eds) *Towards a Service-Based Internet, LNCS* vol. 6994. Berlin, Heidelberg: Springer, pp.62-74.
- Razavian, S.M., H. Khani, N. Yazdani, and F. Ghassemi 2013. An Analysis of Vendor Lock-in Problem in Cloud Storage. *3rd International Conference on Computer and Knowledge Engineering (ICCKE 2013)*. Mashad, Iran: IEEE.
- Ruan, Keyun 2017. Introducing Cybernomics: A Unifying Economic Framework for the Measurement of Risk. *Computers & Security* 65: 77-89.
- Salies, Evens 2012. Product Innovation when Consumers Have Switching Costs. Chapter 31 in Michael Dietrich and Jackie Krafft, *Handbook on the Economics and Theory of the Firm*. Northampton, MA: Elgar, pp.436-447.
- Shapiro, Carl and Hal R. Varian 1999. *Information Rules. A Strategic Guide to the Networking Economy*. Boston, MA: Harvard Business School Press.

- Subramanian, Nalini, Andrews Jeraraj 2019. Recent Security Challenges in Cloud Computing. *Computers and Electrical Engineering* 71: 28-42.
- Uotila, Juha, Thomas Keil, and Markku Maula 2017. Supply-Side Network Effects and the Development of Information Technology Standards. *MIS Quarterly* 41(1) 1207-1226.
- Varian, Hal R. 2004. Competition and Market Power. In Hal R. Varian, Joseph Farrell, and Carl Shapiro, *The Economics of Information Technology. An Introduction*. Cambridge, UK: Cambridge University Press, pp.1-47.
- Villas-Boas, J. Miguel 2015. A Short Survey on Switching Costs and Dynamic Competition. *International Journal of Research in Marketing* 32(2) 219-222.
- Wilms, Konstantin, Stefan Stieglitz, and Benedikt Müller 2018. Feeling Safe on a Fluffy Cloud – How Cloud Security and Commitment Affect User’s Switching Intention. *Proceedings of the Thirty Ninth Conference on Information Systems*, San Francisco.
- Young, Adam and Moti Yung 1996. Cryptovirology: Extortion-Based Security Threats and Countermeasures. *Proceedings of the 1996 IEEE Symposium on Security and Privacy*. Oakland, CA: IEEE, pp.129-140.

Figure 1: Nash and Stackelberg Equilibria

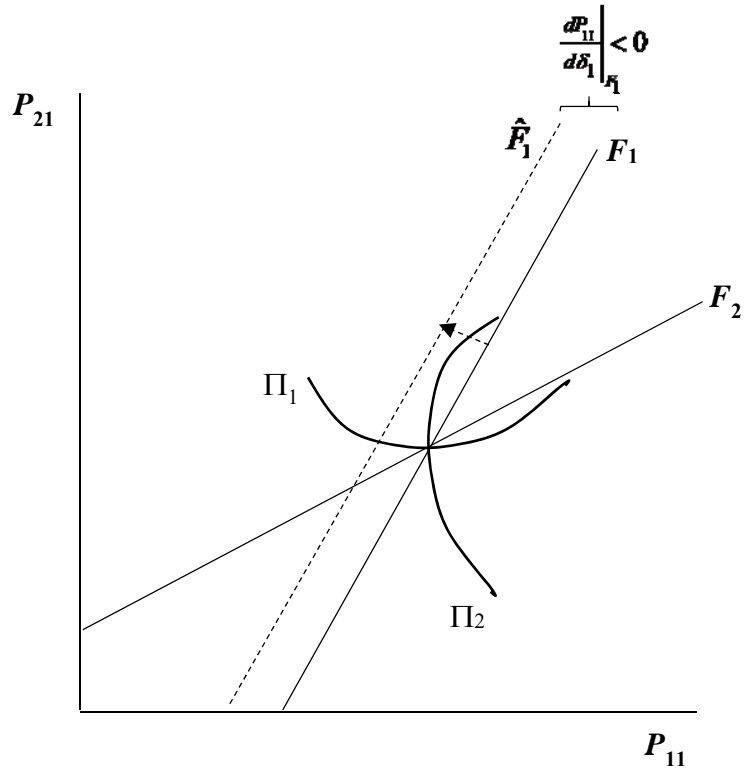


Nash Equilibrium

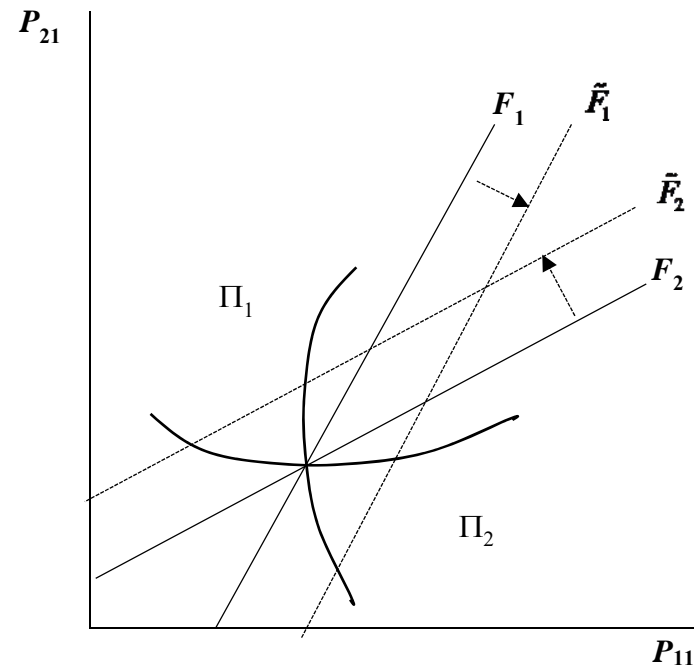


Stackelberg Equilibrium

Figure 2: (Anti-) Lock-In Effects



Unilateral $\uparrow \delta_1$ by CSP 1 User



**Mutually increasing lock-in ($\downarrow \delta_1, \downarrow \delta_2$)
is Pareto-Improving**