The Hidden Cost of Hidden Fees:
A Dynamic Analysis of Price Obfuscation in Online Platforms

We study the effects of a common price obfuscation tactic, namely “shrouding hidden fees” on consumer behavior and platform firm performance. Where traditional economic models of individual firms have shown that obfuscation tactics can be profitable for these firms even in repeated interactions, more recent work in behavioral operations management has argued that these tactics can be harmful not just to consumers but to the firms themselves. We contribute to these studies by explicitly accounting for different aspects of platform value creation, to understand the role and incentives of platform firms as intermediaries to facility the matching process, and by using simulation modeling methods that allow us to expand model boundaries, and study appropriate time horizons. We find evidence to suggest that building consumer trust through disclosure is a dynamic attribute that may be dominated by worse-before better outcomes. The results provide evidence that the platform pricing transparency decisions should differ depending on market and industrial context.

Keywords: online platforms, two-sided markets, network effects, pricing, price obfuscation, consumer behavioral learning.

1. Introduction

Investment in platforms has exploded in recent years, and both consumers and businesses are increasingly engaging with vendors via third party platforms (Parker et al. 2017; Delaboylaye, 2019; Konen and Heckler, 2021; Anderson et al. 2022; Cusamano et al. 2023). At the same time, grievances continue to grow from dissatisfied consumers regarding their perceptions of price gouging and the use of deceptive features in online pricing (Huffman, 2019; Crumley, 2024). Examples abound: online ticket sellers will shroud and pass on to consumers a variety of different surcharges, under the guise of “event fees”, “venue fees”, and “convenience fees”, that are not initially disclosed to consumers. Food delivery apps will hide their "service fees", or tack on "small order fees", and "expanded range fees" only after consumers have been enticed by lower prices. Hotels, *Airbnb*, and other hospitality platforms have started to charge "resort fees", and "cleaning fees" that are disclosed only upon check-out. In many, if not all these cases, taxes are added onto the new price inclusive of fees, adding to consumer's frustrations and difficulties in becoming fully informed of final prices before starting the purchase process. In general, these hidden fees have been widely panned by consumers, and the debate has drawn the attention of the press and regulators alike, and some platforms have begun exploring options to become more transparent (Tumin, 2022; Dickler 2023; Beam, 2024).

The fact that so many of the most popular platform firms continue to employ these tactics, while consumers so vehemently dislike them presents us with an interesting puzzle. We draw across several streams of literatures including marketing, economics, informations systems, and behavioral operations management to explore how platform firm incentives, competitive pressures, and their current strategy, influence platforms' decisions to obfuscate prices, or alternately, to buck trends and try to become more transparent. Following Akerloff and Schiller (2015) we will define price obfuscation as "*any tactic used by firms with the intention of preventing customers from becoming fully informed about market prices*." For a comprehensive categorization of the various types of deceptive features in online platforms, refer to Benet Chiles (2017) and Johnen and Somogyi (2021). In this study, we will focus on "price dripping" as a form of price obfuscation, whereby a firm advertises only part of a product's price up front and then reveals additional mandatory fees or surcharges as the consumer moves through the purchase process (Santana et al. 2020).

We develop a model of platform firm choice and consumer behavioral response and use it to analyze the performance dynamics of shrouding versus transparent platforms. Simulation modeling allows us to expand on existing theory by accounting for more nuanced consumer behavioral responses, multiple feedbacks, and repeated interactions. Throughout this study, we'll use a digital delivery platform (an online ticket reseller) to illustrate our results. The rest of our paper is organized as follows: *Section 2* presents a summarized review of the extant relevant literature; *Section 3* presents the methodology used and describes our simulation model; *Section 4* presents simulation results; insights from the model, and potential managerial policies are discussed in *Section 5*. We conclude with some additional observations, and extensions for future work in *Section 6*.

2. Motivation and Literature Review

The current body of research on price obfuscation spans distinct literatures, from economics, to marketing, to information systems, with each disciple developing different frameworks, methods, and definitions of the phenomenon under study (Bennet Chiles, 2017). Our study spans across disciplines and brings together separate literatures on price shrouding and two-sided platforms.

Theoretical and empirical evidence from work in economics and marketing has shown that companies can strategically hide or obscure certain aspects of prices to exploit consumer shortsightedness, resulting in higher firm profits, which can persist even in repeated purchases (Ellison and Ellison, 2009). Studies have shown that these obfuscation tactics are individually rational for oligopolistic firms due to high search costs for consumers (Gabaix and Laibson, 2006), and experiments have concluded that disclosing fees upfront can reduce both the quantity and the quality of consumer purchases, and that efforts to increase salience cause revenues to drop (Blake et al. 2021). "There is no reason to expect new visitors to a site to have correct beliefs about fees, and once they have their sights on an item, letting go of it becomes hard—as scores of studies in behavioral economics have shown. People end up making purchases that in hindsight they would not have made" (Foy, 2021).

However, transparent price disclosure and increasing the salience of secondary attributes can eliminate price framing effects, leading to increased revenues for sellers (Brown et al. 2010). And recent work in behavioral operations management suggests that these obfuscation tactics can be harmful not only to consumers, but also to the firms that engage in them. Various field experiments have shown that firms can create value for themselves and their customers by increasing operational and cost transparency, and through other acts of sensitive disclosure (Mohan et al. 2020; Buell et al. 2021).

Adding to the complexity, existing theories offer different conclusions with respect to the effect that competition should have on a firm's propensity to obfuscate prices, and the literature studying the role of price transparency in online platforms is still nascent (Blake et al. 2021; Bennet Chiles 2021). Where they have been studied, the focus has been on the strength of the cross-side network effects that drive platform growth, showing that in some cases, platforms may have even stronger incentives than to shroud complementor fees than even the complementors themselves (Johnen and Somogi, 2022).

Interestingly, though many of the most popular online ticket seller platforms (e.g.: *Booking.com, Kayak.com, StubHub*, and *Ticketmaster*) purport to reduce search costs and frictions to facilitate price comparisons for their consumers, "price dripping" tactics, whereby additional mandatory fees are not disclosed upfront but rather added-on or "dripped" as the consumer progresses through the purchase process have now become so ubiquitous as to have drawn the ire of regulators (Dickler, 2023).

Platforms can increase competition by consolidating price information from multiple firms. To counteract this intensified competition, firms often employ intricate pricing strategies. However, platforms have some influence over the extent of pricing complexity adopted by firms since they earn revenue from firms paying to be featured on their platform, creating an incentive to permit obfuscation. (Mamadehussene, 2020). Overall, while the notion that consumers may punish firms for price obfuscation (and deceptive behavior more generally) is hardly new surprisingly little research exists to support it. (Bennet Chiles, 2017).

Although many of the most widely used matching platforms offer to help reduce consumer search costs, and efficiently find lowest prices, empirical evidence from consumer engagement with these platforms shows that "hidden fees" are ubiquitous. This occurs even when the marginal cost of one additional ticket to the platform is vanishingly small.

Figure 1 below provides an illustration of price dripping and hidden fees on the largest online ticket reselling platform (*Ticketmaster*).

Figure 1: Price-Dripping and Hidden Fees on Ticketmaster App.

Fig 1.1

Fig 1.2

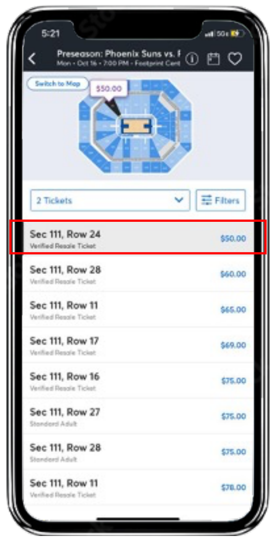


Fig 1.3

Fig. 1.4

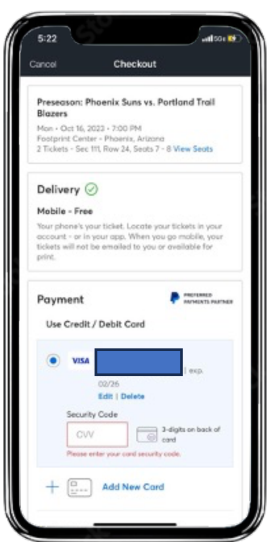


Fig 1.5

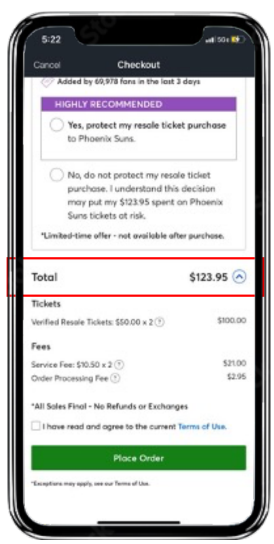


Fig 1.6

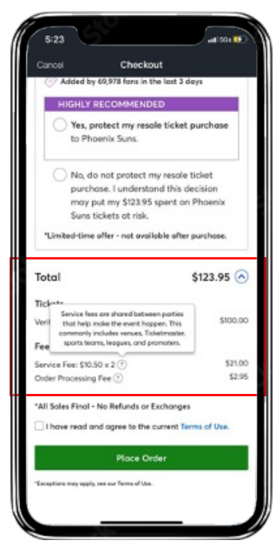


Figure 1.1-1.6 shows a sequence of screen grabs from Ticketmaster's App. These illustrate the purchase process. Initially, potential consumers search on the platform, and are exposed to initial or "visible prices" that they use to make their selections. As they continue to the purchase process, previously undisclosed or "hidden fees" are added, or "dripped". Once the full price has been revealed, the consumer has invested time and effort, and may be induced to pay above their original intended willingness to pay. In this case, the total of the hidden fees is upwards of 22% of the initial quoted (visible) price.

Our work augments previously existing models with behavioral consumer learning to further understand the effects of obfuscation on consumer loyalty and firm performance and contributes to our understanding of the costs of price obfuscation more generally.

3. Methods and Modeling

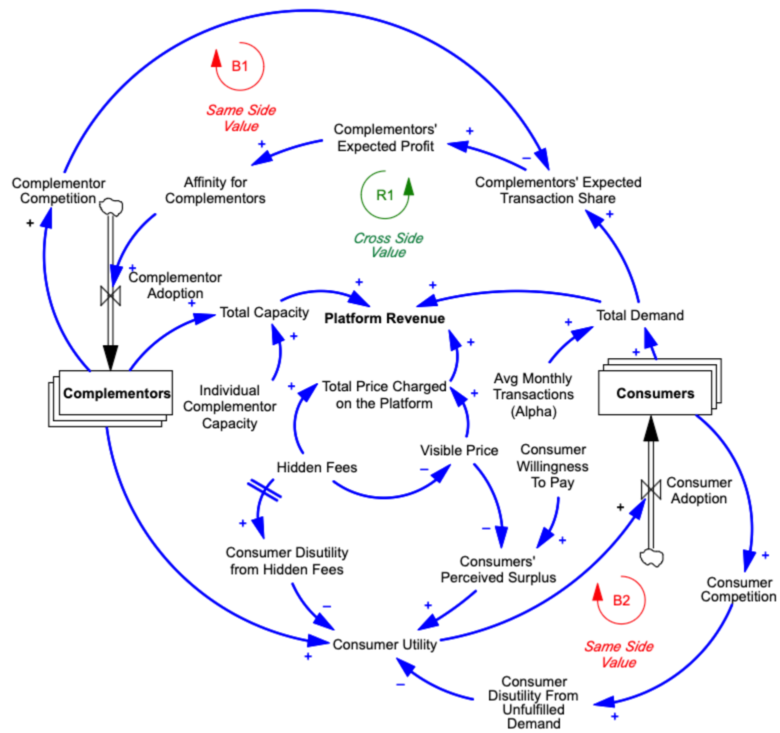
We consider a stylized and parsimonious model of platform competition in a two-sided market. In our model, up to two platforms (P_1, P_2) compete for a limited pool of potential consumers $B(t)$, where the *B* stands for Buyers (the demand side of the market) and a limited pool of potential complementors $S(t)$, where the *S* stands for *Sellers* (or the supply side of the market). Following our motivating example of ticket resellers on a matching platform, complementors list their tickets for sale on the platform, and consumers use the platform's website or mobile App to evaluate the product offerings, make comparisons, and ultimately make ticket purchases for the event of their choosing. Thus, the platforms act as intermediaries, facilitating matches, and charging fees to one (or both) sides of the market whenever a transaction occurs.

The Value Creation Lens

We adopt the Value Creation Lens (Anderson et al. 2022) as a framework to understand platform attractiveness and user (both complementor and consumer) utility. This framework, grounded in theory, creates a better understanding of the dynamics of platform value creation and its drivers for growth, by separating the platform's value creation into 3 mutually exclusive and collectively exhaustive components: the *cross-side* value, the *same-side* value and the *stand-alone* value. Here, the cross-side value refers to the change in attractiveness provided by having one additional participant on the other side of the market, the same side value refers to the change in attractiveness resulting from one additional participant on the same side of the market, and the stand-alone value refers to the change in attractiveness provided by the platform regardless of the participants. Using our motivating example of a ticket resale platform, and taking the perspective of a potential consumer (buyer), the cross-side value of the platform refers to the increase in utility of having one more seller to choose from, the same-side value refers to the decrease in utility of having one more competing buyer, and the stand-alone value refers to the potential for the platform to reinvest (or forgo) some of its revenues initial revenues to create a smoother search and matching process -potentially by increasing price transparency. Critically, most platform studies have focused on the strength of the cross-side network effects, while in this context, there is a potential for high attractiveness and differentiation from stand-alone value propositions.

To illustrate further, we present a simplified causal loop diagram for the model and use it to explain key components and feedback loops. For clarity, some of the mechanisms have been summarized, but full model equations are present in the Annex. Figure 2 below, that shows the various ways in which a ticket-seller matching platforms can create value around a pricing decision:

Figure 2: The Value Creation Lens



The cross-side network effects (Reinforcing Loop R1) are still at the core of our model, linking consumer and complementor participation. As complementors join the platform to offer their products, both quantity and variety increase, which makes the platform more attractive to consumers. With higher consumer utility, more consumers will join, ultimately driving more complementors to join in a reinforcing loop. However, from it is also clear that utility can be derived from other sources.

Specifically, we also consider that the platform can make some strategic "stand-alone" decisions, namely, deciding whether to hide (shroud) part of their prices, or to be completely transparent about their fee structure. Specifically, while consumers may first anchor on the initial Visible Price and derive a Perceived Consumer Surplus (Johnen and Somogy, 2022) if their original Willingness To Pay is higher, we also account for the fact that consumers will face a Disutility from Hidden Fees. Critically, this only occurs after engaging with the platform, so that the updates occur with a delay. The diagram also underscores a key feature of our model, which considers the role of competition or cooperation amongst same side participants in platforms. For our setting, same-side competition amongst consumers (buyers) and complementors (sellers) lowers their respective utilities.

Brief Overview of the Model Structure:

Below we provide also provide a brief overview of the model structure. Our formulations are grounded in the Information Systems literature and, in particular, we use standard System Dynamics formulations where they are appropriate. We focus on augmenting the traditional game theoretic models of platform competition and add elements of consumer behavioral learning to the model. A summary of key model assumptions is as follows:

- **Assumption 1 (Variable normalization):** Consumer and complementor market sizes can be normalized to 1 (i.e. $B(t)) \leq 1$, and $S(t)) \leq 1$, respectively) without loss of generality.
- **Assumption 2 (Installed base):** At *t*=0, the platforms have no installed base of consumers or complementors (i.e. $B(t)) = 0$, and $S(t)) = 0$, respectively), which means there is no "piggybacking" from an existing user base (Dou and Wu, 2021).
- **Assumption 3 (Complementor's capacity):** We assume that the complementors are identical in their capacities, and the costs they face. Their decision to join the platform is based on an expectation of future profits.

Pricing:

Final Sales Price: The final price that consumers pay on the platform is composed of 2 parts, the complementor's service price, and the platform's margin.

$$p_{final} = p_{service} + p_{platform} \tag{1}$$

Price Shrouding: A parsimonious model of price shrouding requires only that the platform's margin be understood as composed of an initially visible price, and a hidden fee that is initially shrouded, and only revealed after the consumer has gone through the majority of the purchase process:

$$p_{platform} = p_{visible} + p_{hidden} \tag{2}$$

Such that:

$$p_{final} = p_{service} + p_{visible} + p_{hidden} \tag{3}$$

Note that a transparent platform will set $p_{hidden} = 0$.

Platform revenue: In the most general case, platforms could collect revenue via subscription fees from both the consumer and complementor sides of the market. However, in more realistic representation for a matching platform, revenues are determined by the number of transactions. In our baseline formulation we consider that platform revenues are a product of the final sales price and the number of transactions $Q(t)$, net of the the costs to the platform $C(t)$.

$$\pi_{platform} = p_{final} \cdot Q(t) - C(t) \tag{4}$$

Where the *actual number of monthly transactions on the platform* $Q(t)$ is constrained by the total demand and the total capacity:

$$Q(t) = min[Demand(t), Total\ Capacity(t)] \tag{5}$$

And the in turn, *Demand* is calculated as the product of α*, the average number of transactions per person per month*, and the number of consumers $B(t)$ on the platform.

$$Demand(t) = \alpha \cdot B(t) \tag{6}$$

And the *Total Capacity* is given by each individual complementors' capacity, multiplied by the number of complementors $S(t)$ on the platform:

$$Total\ Capacity(t) = Capacity_S \cdot S(t) \tag{7}$$

We have assumed that each individual complementor's capacity is identical. As such, we formulate the necessary capacity that each complementor must have to clear the market in case where every potential consumer B_{max} and complementor S_{max} joined the market as:

$$Capacity_S = \alpha \cdot \frac{B_{max}}{S_{max}} \cdot (1 + \gamma) \tag{8}$$

Where the parameter γ is a measure of the extra fractional supply chain capacity, which allows us to consider cases where either Total Capacity, or Demand are the active constraints on sales.

Finally, combining (4)-(8), we arrive at the formulation for platform profits:

$$\pi_{platform} = p_{final} \cdot min\left[\alpha \cdot B(t), \alpha \cdot \frac{B_{max}}{S_{max}}(1+\gamma)S(t)\right] - C(t) \tag{10}$$

Consumer utility and participation: Platforms compete for consumers. In line with previous literature, we adopt an additive formulation for of the consumer utility function (Anderson et al 2014, Tan et al. 2020, Tan et al. 2023). Following the value creation framework, we have that utility can come from: cross-side network effects, same-side network effects, and strategic decisions that the platform makes which can create stand-alone value for consumers. Since our principal interest is in participation decisions that are subject to price perceptions, and specifically hidden fees, we augment current models with a behaviorally realistic accounting of consumer's perceptions of hidden fees.

Where previous models assume that consumers' utility increases with additional complementor participation (positive cross-side network effects), and that their purchasing decisions are anchored on the initially quote price $p_{visible}$, whereby perceived surplus is derived from the difference between their initially stated willingness to pay p_{wtp} and $p_{visible}$, we introduce 2 important modifications: firstly, while "naïve" consumers may be induced to purchase even above their originally stated willingness to pay via hidden fees, they will also incur a disutility at the end of the purchase process from the lack of transparency. We explicitly account for this term. Additionally, in order to model the consumers' utility more realistically, we also introduce the concept of a Fulfillment Ratio, to indicate how much of the consumers' demand *D(t),* can be met on the platform by the complementor's capacity:

$$FR = \frac{Q(t)}{D(t)} \tag{11}$$

A Fulfillment Ratio that is less than 1, indicates that there is an imbalance between supply and demand, potentially resulting in dissatisfied customers. This incorporates a negative same-side effect due to increased competition.

At a high level, we have that:

$$U_B(t) = (U_{CrossSide}(t) - U_{SameSide}(t) + U_{PerceivedSurplus}(t) - U_{HiddenFee}) \tag{12}$$

And we operationalize it in the following way:

$$U_B(t) = [MS_S(t)^{\omega_{cs}} + \omega_{price} \cdot \alpha \cdot \frac{p_{wtp} - p_{service} - p_{visible}(t) - (\omega_{pen} \cdot p_{hidden}(t))}{p_{wtp}}] \cdot FR - \omega_{shortage} \cdot (1 - FR) \tag{13}$$

This formulation considers diminishing returns on the cross-side network effects, penalizes platforms that don't balance supply and demand correctly, and includes a component for the perceived price surplus, and a penalty on shrouding.

Consumer participation level at time *t*, here $MS_B(t)$, for the market share of buyers, is determined by comparing the relative attractiveness of each platform to the total attractiveness of all options, including an outside option of not participating in the platform markets, which we denote as ρ_B.

In our motivating example, this would be akin to having consumers buy the tickets directly from a third-party seller, for example, by conducting the transaction outside of the venue. Note well that if the size of the consumer market is normalized to 1, consumer participation $B(t)$ is equivalent to the platform's market share on the consumer side. We first calculate the indicated consumer market share at time *t*, $\widehat{MS_B}(t)$, which represents the expected consumer market share, given each platforms' current value proposition.

We assume that the platform's expected market share on the consumer side is determined based on the logit choice model (McFadden, 1986), which has been used extensively in the literature in Information Systems (Anderson et al. 2023) and System Dynamics (Sterman, 2000). According to this formulation, the indicated consumer market share is given by:

$$\widehat{MS_B}(t) = \frac{e^{\beta_B \cdot U_B(t)}}{\sum e^{\beta_B \cdot U_B(t)} + e^{\beta_B \cdot \rho_B(t)}} \tag{14}$$

Where β_B is the logit coefficient for consumers. The model has the flexibility to represent a differentiated market, such that a higher β_B means that the competition amongst the platforms (and the outside option) is more intense, and consumers are sensitive to smaller differences in utility for their participation choices. The inverse of β_B is analogous to the transport cost in the Hotelling model (Tan et al. 2023).

Finally, consumer participation level is a stock that can change over time in the following way: when the indicated consumer market share $\widehat{MS_B}(t)$ is greater (less) than the current consumer market share $MS_B(t)$, the system will move towards the indicated market share $\widehat{MS_B}(t)$ and $MS_B(t)$ will increase (decrease) with some delay. We allow for the delay for consumers adopting the platform τ_{DA} to be different from the delay with which they exit τ_{DE}. Thus, the change in $MS_B(t)$, is given by:

$$MS'_B(t) = \begin{cases} \dfrac{\widehat{MS_B}(t) - MS_B(t)}{\tau_{BA}} & if \widehat{MS_B}(t) \geq MS_B(t) \\ \dfrac{\widehat{MS_B}(t) - MS_B(t)}{\tau_{BE}} & otherwise \end{cases} \tag{15}$$

Consumer learning: Consumers are initially "naïve", and do not have an expectation of hidden fees. However, through interacting with the shrouding platforms over time, they will become informed of the hidden fees and will begin to price them in by adding their expectation to the initial quoted price. We use an exponential smoothing formulation, typically used in System Dynamics models (Sterman, 2000) via which consumers will gradually form a perception of hidden fees with some time delay $\tau_{perceive\ fees}$:

$$p'_{perceived} = \frac{p_{initial} + p_{perceived\ hiddenfee}}{\tau_{perceive\ fees}} \tag{16}$$

And the time delay can depend on how frequently the consumers interact with the platform, and how salient those prices are to them.

Complementor Expected Profits and Participation: Platforms compete for sellers as well. Where previous work in operations management and in information systems literature has adopted additive forms for the complementors' utility function (Anderson et al. 2014, Tan et al. 2023), our setting requires a more behaviorally realistic formulation. Complementors on platforms generally differ from consumers, in that they are driven primarily by profit expectations. In this sense, complementors are akin to small businesses looking to maximize expected profits.

Complementors' expected profit is increasing in actual number of transactions $Q(t)$ and decreasing in the number of competing complementors that have also joined the platform $S(t)$.

$$E[\Pi_S(t)] = \frac{Q(t)}{S(t)} \cdot \left(p_{service} - c_{service} - c_{fees}\right) \tag{17}$$

Where $c_{service}$ is the cost of the service to the complementor and c_{fees} are the (potential) fees charged by the platform to complementors. Note they are currently set to 0 without loss of generality. If we call the complementors' expected profit per transaction π_s, we have that:

$$E[\Pi_S(t)] = \frac{Q(t)}{S(t)} \cdot \pi_s \tag{18}$$

In this model, we assume that complementors have the same sales costs for their services across platforms, and are charged the same fees across the platforms, so that the relevant elements of the complementors' utility function is given by the three components mentioned above.

We again assume that the platform's expected market share on the complementor side is determined based on the logit choice model (McFadden, 1986, Anderson et al. 2023, Sterman, 2000), By symmetry with the consumers, the indicated complementor market share is given by:

$$\widehat{MS}_S(t) = \frac{e^{\beta_S \cdot U_S(t)}}{\sum e^{\beta_S \cdot U_S(t)} + e^{\beta_S \cdot \rho_S(t)}} \tag{19}$$

Where β_S is the logit coefficient for complementors. Again, the model has the flexibility to represent a differentiated market, such that a higher β_S means that the competition is more intense.

Finally, complementor participation level is a stock that can change over time in the following way: when the indicated complementor market share $\widehat{MS}_S(t)$ is greater (less) than the current complementor market share $MS_S(t)$, the system will move towards the indicated market share $\widehat{MS}_S(t)$ and $MS_S(t)$ will increase (decrease) with some delay. We model allows the delay for complementors adopting the platform τ_{SA} to be different from the delay with which they exit τ_{SE}. Thus, the change in $MS_S(t)$ is given by:

$$MS_S'(t) = \begin{cases} \dfrac{\widehat{MS}_S(t) - MS_S(t)}{\tau_{SA}} & if \widehat{MS}_S(t) \geq MS_S(t) \\ \dfrac{\widehat{MS}_S(t) - MS_S(t)}{\tau_{SE}} & otherwise \end{cases} \tag{20}$$

The model's key parameter values are shown in the table below. The implementation of the model in Vensim includes additional formulations, e.g. to ensure robustness to extreme conditions. For clarity, the complete model formulations and parameter values are provided in the Appendix and the accompanying model.

Table 1: Key Model Variables and Parameter Values

Variables	***Description***	***Base Value****
$P_{1,2}$	Platforms.	-
$MS_s(t)$	Complementor Market share (Dimensionless)	-
$MS_B(t)$	Consumer Market share (Dimensionless)	-
$S(t)$	Complementors. (People)	-
$B(t)$	Consumers. (People)	-
$p_{service}$	The price at which the complementors sell to the platform($)	1
$p_{visible}$	The part of the final price that is initially quoted to consumers($)	1
p_{hidden}	The part of the final price that is initially hidden from consumers ($)	0.3
p_{wtp}	Consumer's original willingness to pay. ($)	1.1
α	Average monthly transactions per consumer. (Transactions/month/person)	1
ω_{cs}	Coefficient of sensitivity to cross-side network effects for consumers [0,1] (Dmnl)	0.5
ω_{price}	Coefficient of consumer utility from average perceived price surplus (Dimensionless)	1
ω_{fee}	Coefficient of consumer disutility hidden fees (Dimensionless)	2
$\omega_{shortage}$	Coefficient of consumer disutility from unfulfilled demand (Dimensionless)	0.5
γ	Extra fractional capacity (Dimensionless)	0
ρ_S	Utility of the outside option for complementors (Dimensionless)	0
ρ_B	Utility of the outside option for consumers (Dimensionless)	0
β_S	Logic coefficient for complementors (Dimensionless)	2
β_B	Logic coefficient for consumers (Dimensionless)	2
τ_{us}	Unshrouding time. (Months)	12
$\tau_{perceivefees}$	Time to become informed of hidden fees (Months)	6

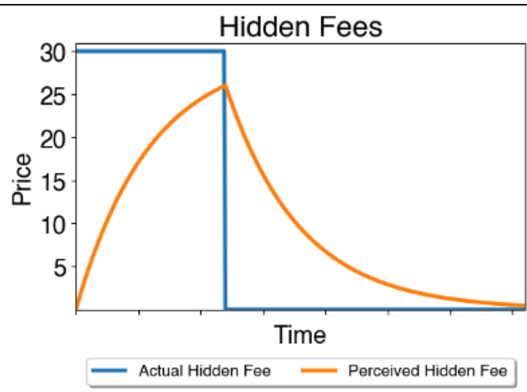
*Parameter Base values have been informed by previous literature on B2B and transaction platforms (Anderson et al. 2022; Koenen and Heckler, 2020; Zhu and Iansiti, 2019). We also draw from Prospect Theory, and account for the fact that loses loom about twice as large as gains (Kahneman and Tversky. Importantly, we are not calibrating a model to data, but rather are interested in the magnitudes and ratios of the parameter values. Sensitivity analysis is performed in section 4.

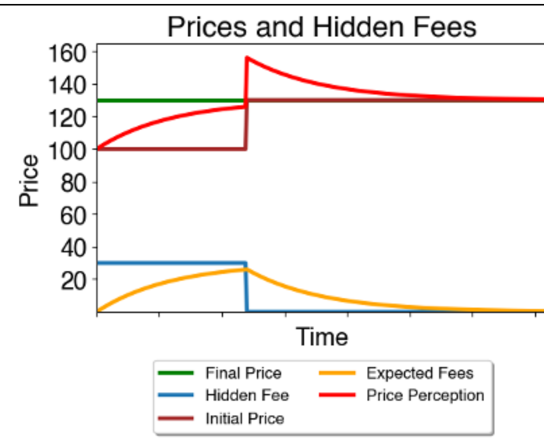
4. Simulation Results

Implications of Price Perceptions

One key contribution of this work is to include a dynamic formulation of consumer price perceptions and consider its impact on consumer decision making. Where previous models have assumed a set fraction of “naïve” consumers who are uninformed of hidden fees, and a set fraction of “sophisticated” consumers who are aware, we allow this fraction to vary dynamically, via engagement with the platform. The larger the platform, the more frequent the purchases, or the larger the hidden fees, the faster that consumers will become “sophisticated”.

Figure 3: Modeling Consumer Price Perceptions





It takes time for consumers to become aware of potential hidden fees on the platform. In this example, we set the initial hidden fee to 30%, in line with our exploration of platform hidden fees across industries. Initially, consumers are unaware of the hidden fee, and only become informed as they interact with the platform. The orange line of consumer perceptions exponentially approaches the blue line of the actual hidden fee.

The Final Price (green line) that the platform charges consumers is composed of two parts: the Initial or Visible Price (maroon line) plus the Hidden Fee (blue line). A platform that wishes to maintain Final Price (green line) which experimenting with reducing Hidden Fees must then increase their Initial or Visible Price. Consumers who have anchored on the hidden fee will expect higher total prices.

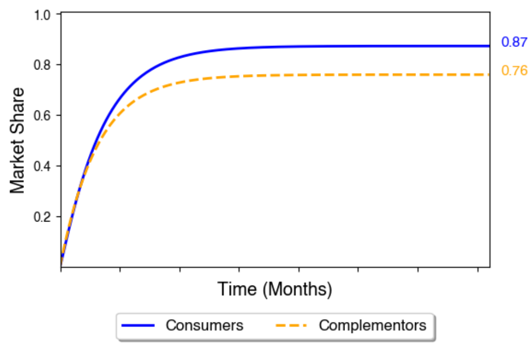
Given enough time and engagement, consumers will become fully aware of the hidden fees, and price it into their decision making. Importantly, price perceptions are “sticky”, and if the platform decides to unshroud (drop the hidden fees) and become transparent, consumer price perceptions will remain high until they engage with the platform sufficiently, however there are important dynamics in the transient that have important implications for firm success.

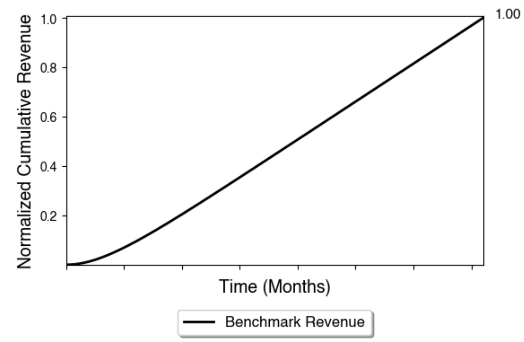
When a platform becomes transparent and forgoes the Hidden Fee component of their Final Price, they must now transfer the same amount to their Visible Price which is initially quoted to consumers if they wish to maintain their revenue per transaction constant. If consumers have grown accustomed to hidden fees on the platform (or even their competitor's) platforms, then the Unshrouding platform will initially be compared unfavorably by consumers, who now face a higher Visible Price, and still expect Hidden Fees on the back end. This consumer response to shrouding, and price perceptions, helps explain nuances in platform firm price transparency decisions. In line with previous work, we show platform growth dynamics, but we are interested in the differences that arise from price transparency decisions. We run our model for a simulated period of 3 years. At $t_{us} = 12$ months, P_1 can decide to unshroud fees and become transparent.

Simulation Case Studies

We begin by exploring the simplest case of a monopolistic platform that shrouds its fees, in a setting where there is no consumer behavioral learning. Previous works have shown that it is optimal for firms in these settings to price shroud, and our model can replicate this behavior. Figure 4 below shows the results:

Figure 4: Case 1: Monopoly Platform, Shrouding, No Consumer Learning





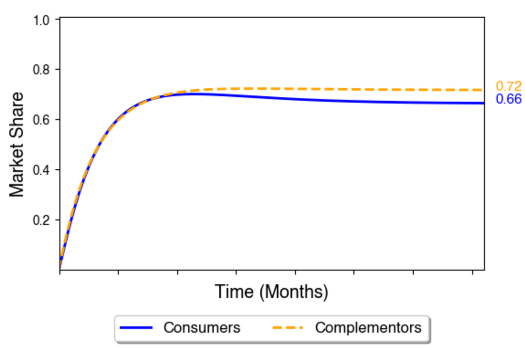
We plot consumer (blue line) and complementor (orange line) adoption, and show the respective market shares. In the monopolistic case, the fraction of consumers and complementors that is not on P_1 finds the outside option more attractive. In this case, Consumers derive a higher Utility $(U_B \approx 1)$ relative to the Outside Option $\rho_B = 0$, which results in an 0.87-0.13 market split between the monopolist and the outside option. In this scenario, most of the U_B comes from cross-side network effects.

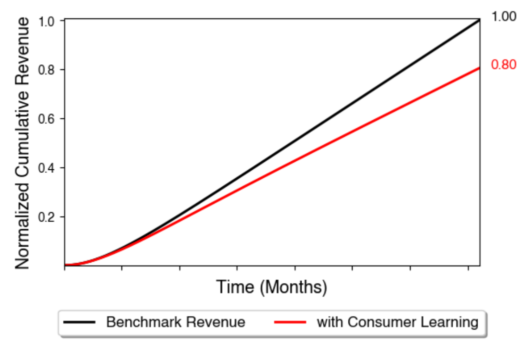
Revenues grow as the installed bases increases. Once market share has reached equilibrium, revenues for the platform remain constant, and the slope for Normalized Cumulative Revenue becomes a straight line. We have performed the normalization to use as a benchmark for the different scenarios we will explore below.

In the absence of consumer behavioral learning (updating expectations about hidden fees) it is optimal for monopolistic platforms to price shroud provided the hidden fee is not so large that the outside option of quitting the platform altogether becomes more attractive. In this case, platforms may extract additional revenues from consumers even above their original stated willingness to pay (Ellison and Ellison, 2006). Since consumers do not become informed, or "sophisticated" over time, this strategy will remain profitable even in repeated interactions.

We now proceed to study the case of a monopoly platform that engages in price shrouding, in a setting where consumers do become sophisticated (i.e. learn about the hidden fees and incorporate them into their pricing expectations over time). Our theory predicts that informed consumers will now compare their expected (higher) price with the outside option, thus reducing the relative attractiveness of the platform against the outside option. Figure 5 shows results:

Figure 5: Case 2: Monopoly Platform, Shrouding, Introduction of Consumer Behavioral Learning



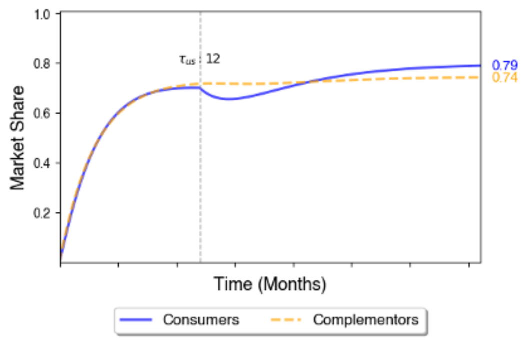


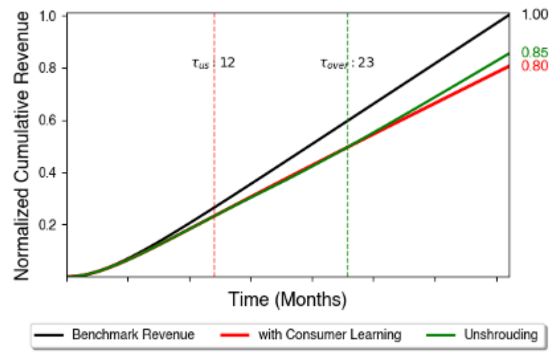
We see that consumer (blue line) market share initially grows, as consumers are "naïve" about the hidden fees. However, we note the growth is slower than for the monopoly case. As consumers transact on the platform, they are becoming aware of the hidden fees, their Disutility from Hidden Fees increases, and as such the total attractiveness of the platform drops. This lower number of consumers drives slower adoption and a lower total installed base of complementors when compared against Figure 4.

We see that total revenues in this case are lower than in the benchmark case when all consumers are naïve. This follows from the fact that the platform has a lower installed base of both consumers and complementors, which lowers the transaction volume and ultimately reduces revenues. This is a direct consequences of the fact that a larger percentage of consumers now finds the outside option (not participating in the platform attractive).

We can now continue to build on these examples and explore the case of a monopolistic platform, in a setting with consumer behavioral learning, that chooses to unshroud prices, becoming transparent to capture a larger market share.

Figure 6: Case 3: Monopoly Platform, Shrouding to Unshrouding, Consumer Behavioral Learning





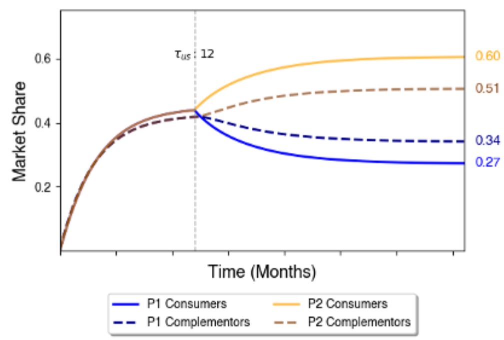
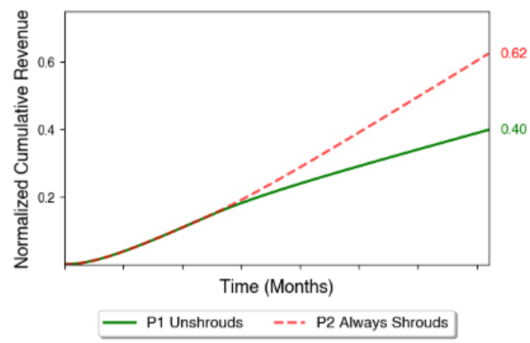
Consumers and complementors initially follow a similar dynamic as in Figures 4 and 5. At time τ_{us}, the platform unshrouds its prices, and becomes transparent. By including its previously hidden fee into its initial quoted price the platform first looks more expensive and less attractive compared to the outside option and a larger exodus of consumers occurs. With some delay, there is a slight impact to complementors as well, due to the strength of the cross-side. Critically, after enough time has passed, consumers learn that the platform is transparent and return to the platform. Preferring transparency to shrouding. This further drives consumer adoption, and the platform can achieve a higher market share than in Figure 5.

We see that platform revenues (green line) initially fall below the previous scenario (red line) as the installed base is reduced. However, over time, the transparent strategy overtakes the shrouding strategy and becomes more profitable. In this setting, it takes the platform almost 11 months after unshrouding for cumulative revenues to surpass the previous scenario. But because the platform is able to win back more market share, revenues in the periods going forward almost match the benchmark case.

In effect, when we introduce consumer behavioral learning, it is no longer optimal to shroud prices even for a monopolistic platform. If the hidden fees are above a threshold value, the outside option is the most attractive option, and the platform misses out on potential revenues. However, as long as the hidden fees are not sufficiently high, some consumers will remain on the platform, and those will drive enough complementor adoption to sustain it in equilibrium. This provides further rationale for assuming that engaging in shrouding is profitable for firms that have enough market power.

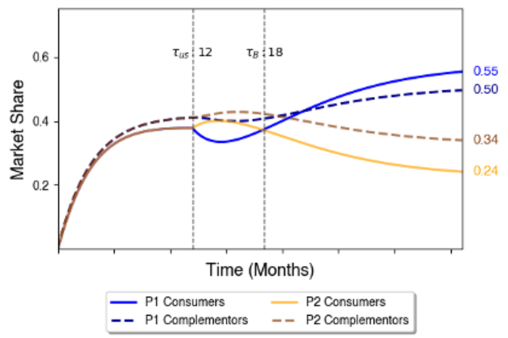
Interestingly, even in a monopoly setting, a platform that has previously been shrouding fees and moves to disclose will face a challenge as it will have to educate consumers about its new price structure. That is, consumers who have previously realized the existence of hidden fees on the platform and even come to expect them, will continue to price them in, even when the platform initially moves to become transparent. To become transparent, and maintain profitability, the platform will need to move the hidden fee into the upfront price. Thus, even though total price remains the same, by removing the now expected hidden fees and increasing the initial quoted price the platform will look more expensive to consumers who will still price in a hidden fee until they interact with the platform enough to become sophisticated in this new sense. Ultimately though, more consumers will flock to the platform than in the previous scenario. We can show then that if firms are willing (and able) to weather the initial lower revenues, they will ultimately have a higher payoff.

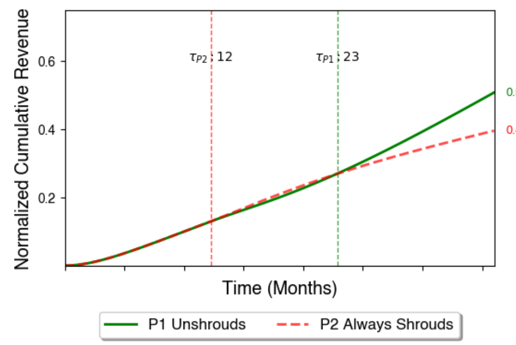
Now, we consider an illustrative case of platform competition. In this scenario, P_1 and P_2 are in competition. If platform offerings are equally attractive, and if both platforms follow the same strategy, in equilibrium they will split the addressable market (with some consumers preferring the outside option ρ_B to either platform. For illustration we assume that initially both platforms are shrouding prices by dripping their hidden fees into the purchase process, and we explore the dynamics as one platform, in this case P_1, moves to become transparent after one simulated year, at time $\tau_{US} = 12$.

<table>
<tr><td colspan="2">Figure 7: Case 4: Platform Competition, Unshrouding vs. Shrouding, with Naïve Consumers</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>In this representation P_1 (in blue) and P_2 (in orange) are in competition. We start with both platforms shrouding prices in equilibrium, and growing in lock step to split the market equally before P_1 makes the strategic decision to become transparent and unshroud its prices. When P_1 unshrouds it initially looks more expensive (less attractive) and it faces a consumer exodus that also drives away complementors. This market share is claimed by P_2. Because there is no consumer behavioral learning, P_1 never recovers</td><td>Here, the green line is P_1 revenue, while the red line is P_2 revenue. After P_1 unshrouds, it loses market share while P_2 seems to thrive. Since consumers are not accounting for hidden fees, P_2 wins.</td></tr>
</table>

Next, we explore this same competitive scenario, in a more realistic setting, where consumers are learning about the platform's hidden fees, and they experience a disutility from being shrouded to.

Figure 8: Case 5: Platform Competition, Unshrouding v Shrouding, with Consumer Behavioral Learning





In this representation P_2 (in blue) and P_2 (in orange) are in competition. We start with both platforms shrouding prices in equilibrium, and growing in lock step to split the market equally before P_1 decides to become transparent and unshroud its prices. Again, when P_1 unshrouds it initially looks more expensive (less attractive) and it faces a consumer exodus that also drives away complementors. This market share is claimed by P_2. However, and critically absent from previous studies, given enough time, consumers will become informed both of P_2 shrouding and P_1 transparency. At this point, even though there is no difference in their final prices, consumers prefer P_1 because there is no disutility from being shrouded to.

Here again, the green line is P_1 revenue, while the red line is P_2 revenue. After P_1 unshrouds, it loses market share and it stagnates, while P_2 seems to thrive. Overtime however, consumers will become embittered about P_2 hidden fees and will come to realize that P_1 is the transparent option. Even if total prices are the same on both platforms, P_1 will ultimately win.

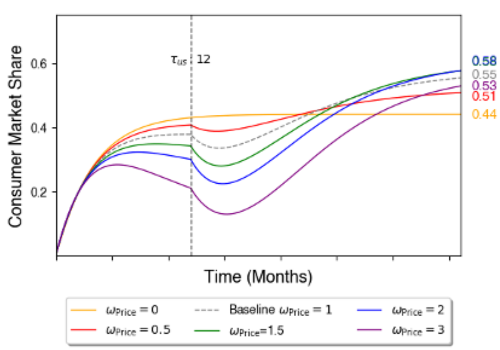
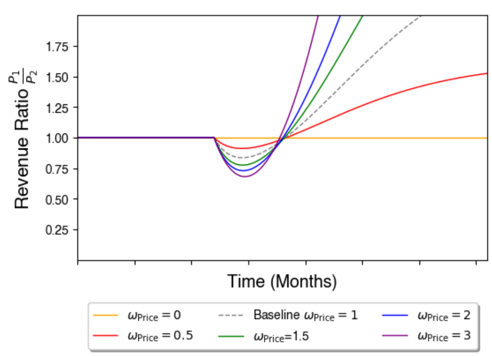
Crucially, in this setting the platform that unshrouds first will experience negative consequences in the short term, as it will initially seem to be the more expensive option for consumers that have come to expect hidden fees on top of a now larger initial price. Over time however, the transparent strategy will pay-off. Which provides further support for the claims that if organizations choose to be deceptive towards their customers, and they are found out, the damages done to their reputation may ultimately overwhelm the short-term gains from the deception. However, firms that decide to become transparent must consider the “worse-before-better” dynamics inherent if the industry standard is to shroud fees. Potentially successful transparency initiatives may therefore be abandoned too early by managers under short-term pressures.

Dynamics of Platform Competition

Our base settings have shown that the decision to shroud prices or become transparent depends not only on the current market environment, but on consumer's priors about hidden fees. We recall from Section 3, that we have modeled the consumer's utility as a combination of 4 components: buyers derive increasing utility from additional sellers, and from their perceived price surplus (anchored on the initially visible price), and in turn face a disutility when they learn of price-dripped hidden fees, or from increased competition by other buyers for the limited supply on the platform. For ease of reference, Equation (12) is reproduced below:

$$U_B(t) = (U_{CrossSide}(t) - U_{SameSide}(t) + U_{PerceivedSurplus}(t) - U_{HiddenFee}) \tag{12}$$

Price sensitive consumers react to hidden fees in two distinct ways. Initially, naïve consumers are drawn in with the promise of a lower price. However, as they interact with the platform repeatedly, they will update their prior on the hidden fees, and will account for them going forward. We explore different outcomes for firms that want to become transparent, when faced with different levels of price sensitive consumers. Figure 9 shows these effects below:

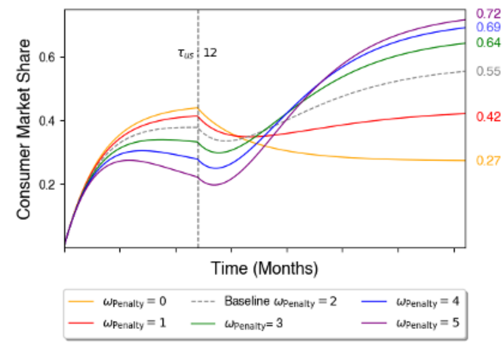
Figure 9: Effects of Price Sensitivity ω_{price}	
	
We model increasing values of consumer price sensitivity (ω_{price}), and we focus on the consumer market share for the transparent platform (MS_{B,P_1}). Compare outcomes against the benchmark case $\omega_{price} = 1$ in dashed gray above.	We show the Revenue Ratio ($\frac{Rev_{P1}}{Rev_{P2}}$), as a summary measure of platform firm performance. A Revenue Ratio greater than 1, indicates benefits from transparency for the unshrouding platform P_1. In general, the greater the consumer price sensitivity (ω_{price}), the greater the benefits from transparency.

When $\omega_{price} = 0$, consumers are completely insensitive to price. Their decision of whether to join a platform, depends solely on the cross-side network effects. Complementors join the platform with the expectation that price taking consumers will buy their products, and buyers derive their utility from matching easily and quickly with a variety of potential sellers. In this setting, less than half (44%) of the potential consumer market share is on Platform P_1 by the end of our time horizon, and an equal amount is on P_2, with about 12% of consumers choosing the outside option. If consumers are increasingly price sensitive, the transparent platform P_1 will have to be prepared to withstand the worse-before-better dynamics inherent in educating consumers about their new lack of hidden fees. For positive values of $\omega_{price} < 1$, consumers will initially derive a large portion of their utility from their perceived buyer surplus (the difference between their original willingness to pay ω_{wtp} and the initially quoted price $p_{visible}$ (net of complementor costs), and lower values of ω_{price} also reduce the disutility from hidden fees $\omega_{penalty}$. However, if consumers are more price sensitive $\omega_{price} > 1$, this magnifies the effect of $\omega_{penalty}$ on the overall $U_B(t)$. For large values of ω_{price}, consumers are initially leaving both platforms in favor of the outside option, as they learn of, and resent the hidden fees. When P_1 unshrouds at $\tau_{US} = 12$, there is an even larger exodus of consumers. Critically, even though there are increasing gains to the revenues for transparent pricing, it may be difficult for firms to weather this additional loss of consumers. Additionally, it's important to note that even if $\omega_{price} \gg baseline\ \omega_{price}$, there are still benefits to transparency, however total cumulative revenues fall dramatically unless the platforms reduce their prices, as they are no longer able to extract surplus from the consumers above the original ω_{wtp}.

Next, we consider the effect of consumer's aversion to hidden fees. We recall from our discussion in Section 3, that a $\omega_{penalty} = 1$ indicates that consumers assign the same weight to hidden fees as they do to the initially quoted price. We know from ample experimental evidence in Prospect Theory that generally, loses loom about twice as large as gains, and this informs our base parameter setting of

$\omega_{penalty} = 2$. However, we are interested in understanding outcomes for a wide range of values of $\omega_{penalty}$. Figure 10 shows these effects below:

<table>
<tr><td colspan="2">Figure 10: Effects of Coefficient of Disutility of Hidden Fee ($\omega_{penalty}$)</td></tr>
<tr><td>



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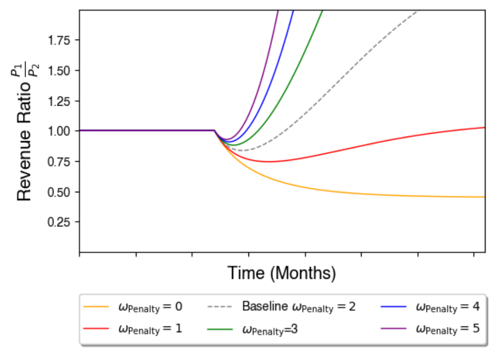
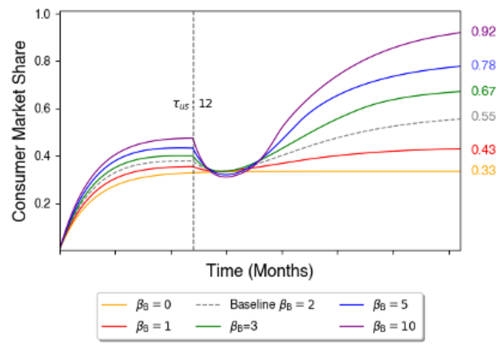


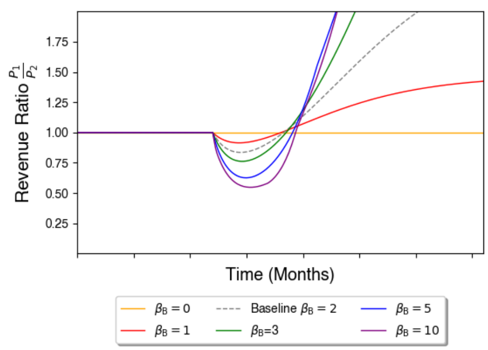
</td></tr>
<tr><td>We model increasing values of consumer disutility on hidden fees ($\omega_{penalty}$), and we focus on the consumer market share for the transparent platform (MS_{B,P_1}). Compare outcomes against the benchmark case $\omega_{penalty} = 2$ in dashed gray above</td><td>We show the Revenue Ratio ($\frac{Rev_{P1}}{Rev_{P2}}$), as a summary measure of platform firm performance. A Revenue Ratio greater than 1, indicates benefits from transparency for the unshrouding platform P_1. In general, the greater the disutility of hidden fees ($\omega_{penalty}$), the greater the benefits from transparency.</td></tr>
</table>

When $\omega_{penalty} = 0$, consumers are completely indifferent to being shrouded to. In this case, it is optimal for platforms to shroud their fees. In fact, whenever $\omega_{penalty} < 1$, the transparent platform underperforms their shrouding counterpart. Notice in Figure 10 that for $\omega_{penalty} < 1$, the value of the Revenue Ratio is also below 1, indicating that the platform is leaving money on the table by switching to transparent pricing. However, for $\omega_{penalty} > 1$, there are increasing gains from transparency. There are also additional pressures for transparency, as consumers with high $\omega_{penalty}$ will be incentivized to leave shrouding platforms in favor of competitors or a constant utility outside option ρ_B.

We have used the logit formulation (McFadden, 1986) to split the consumer market based on affinity to utility. A key structural characteristic of the market is captured in the logic coefficient β_B, which represents the competitiveness of the market. It is important to remember that the logit choice model accounts for consumer heterogeneity in tastes, and as a result, even when $U_B(t) < \rho_B$, some consumers join the platform. Figure 11 illustrates the effects of β_B below:

Figure 11: Effects of Sensitivity to Affinity for Consumers (β_B)



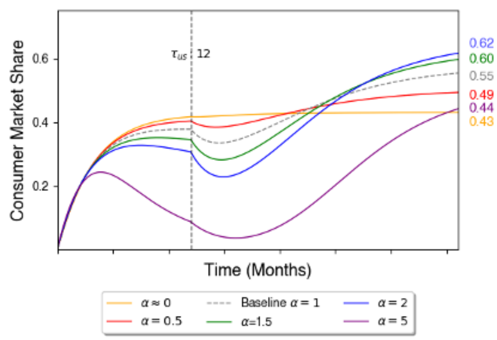


We model increasing values of consumer sensitivity to affinity (β_B), and we focus on the consumer market share for the transparent platform (MS_{B,P_1}). Compare outcomes against the benchmark case $\beta_B = 2$ in dashed gray above

We show the Revenue Ratio ($\frac{Rev_{P1}}{Rev_{P2}}$), as a summary measure of platform firm performance. A Revenue Ratio greater than 1, indicates benefits from transparency for the unshrouding platform P_1. Larger values of β_B

A value of $\beta_B = 0$ represents a completely undifferentiated market. In this extreme case, consumers are insensitive to differing valuations of $U_B(t)$ across the different platforms and the outside option. In this case, the market share will be split equally among all 3 options. This is shown by the orange line in the figure above and the 33% corresponding $MS_B(t)$. However, as β_B increases, consumers are exponentially more sensitive to differences in their affinity valuations of the platforms (and the outside option). Small initial differences in utility compound and drive further adoption. This makes the market fluctuations more pronounced, and the volatility is evidenced by the larger drops in consumer participation upon unshrouding. In a similar fashion, the higher the β_B the more benefits of a transparent strategy once consumers have learned of the "what-you-see-is-what-you-get" pricing that they prefer. Importantly, very high β_B may make it impossible for a firm that wants to pursue a transparent strategy, to successfully navigate the dip. This insight is critical when considering that different industries may be locked in to undesirable equilibria where shrouding is the norm and transparency is suboptimal.

Next, we are interested in the effects of repeated engagement with the platforms on the pressures for obfuscation and transparency. Figure 12 below considers the effects of the average transactions desired by each buyer, which we have previously denoted α:

<table>
<tr><td colspan="2">Figure 12: Effects Average Transactions Desired Per Month Per Person (α)</td></tr>
<tr><td>


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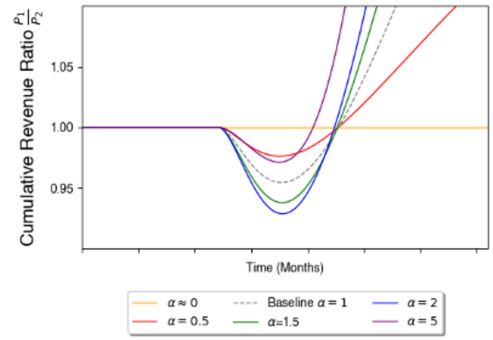
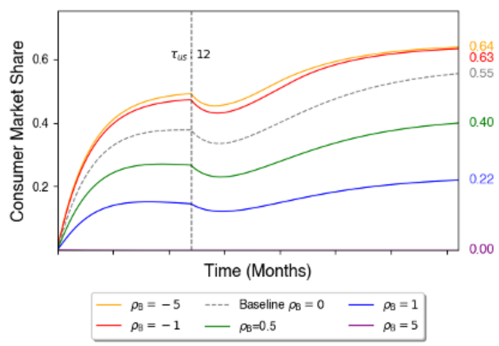


</td></tr>
<tr><td>We model increasing values of average desired transactions (α), and we focus on the consumer market share for the transparent platform (MS_{B,P_1}). Compare outcomes against the benchmark case $\alpha = 1$in dashed gray above</td><td>We show the Revenue Ratio $(\frac{Rev_{P1}}{Rev_{P2}})$, as a summary measure of platform firm performance. A Revenue Ratio greater than 1, indicates benefits from transparency for the unshrouding platform P_1. Larger values of α increase the benefits of transparency, and very large values of α increase the pressure to mitigate the exodus to the outside option ρ_B.</td></tr>
</table>

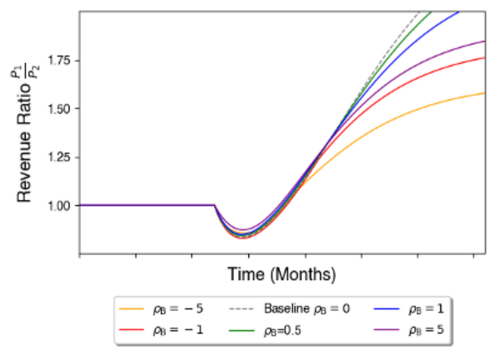
Our baseline value for this model is $\alpha = 1$, which means that consumers demand one transaction per person per month on the platform. Naturally, there will be variation across industries, and consumer heterogeneity, with smaller purchase items (like food delivery) having higher frequency than big ticket items (potentially hotel stays and concerts). If $\alpha = 0$, then no consumers want to transact on the platform, and results are trivial. However, even for very small values of α we can derive meaningful results. A value of $\alpha \approx 0$ indicates that the consumers engage with the platform with very low frequency. As such, there is little chance that they can have a prior on the hidden fee, so there is less value to transparency. but as α increases there is additional value to transparency.

Finally, we are interested in understanding the role of the Outside Option for Consumers ρ_B. Figure 13 shows the effects of variation in the consumer valuation of their Outside Option below:

Figure 13: Effects of Utility of Outside Option for Consumers (ρ_B)



We model increasing values of average desired transactions (ρ_B), and we focus on the consumer market share for the transparent platform (MS_{B,P_1}). Compare outcomes against the benchmark case $\rho_B = 0$ in dashed gray above



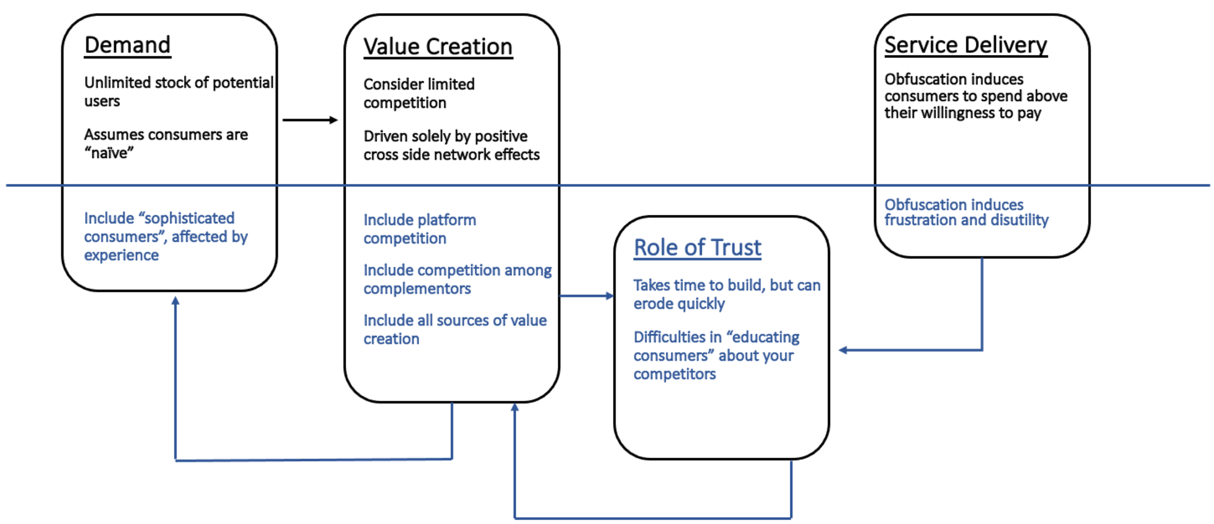
We show the Revenue Ratio ($\frac{Rev_{P1}}{Rev_{P2}}$), as a summary measure of platform firm performance. A Revenue Ratio greater than 1, indicates benefits from transparency for the unshrouding platform P_1. Larger values of ρ_B

Large negative values of ρ_B indicate that consumers don't value the outside option as attractively as they do the platforms. Therefore, as ρ_B becomes increasingly negative, MS_{B,P_i} increases for $i = 1,2$. However, there is a maximum pool of potential consumers, so that there are decreasing returns to an lower and lower values of ρ_B as evidenced in the closeness between the orange and red lines in the Market Share graph above. Importantly, if $\rho_B \ll 1$, but $\rho_S < 1$, the attractiveness of the platform for consumers will be limited by the fact that there is a large imbalance between supply and demand. Fulfillment ratios drop because most complementors would rather sell off platform, and consumers may become discouraged. This underscores the important and difficult task of matching supply and demand for transaction platforms like Uber, Lyft, Ticketmaster, StubHub, and AirBnB. On the other hand, if $\rho_B \gg 1$, then consumers flock to the attractive outside option, and the platform languishes.

5. Discussion and Limitations

In this paper, we have built a parsimonious model of consumer behavioral learning to inform online platform pricing decisions. We have not been prescriptive on whether platforms should shroud prices or become transparent, nor was it our aim to do so in the general case. We argue for expanding model boundaries to include additional complexity between in the form of platform competition and competition in both sides of the market and have especially highlighted the need for taking a long-term view of the dynamics. Observing a long enough time horizon is necessary to fully capture the trade-offs between shrouding and transparency, and the long-term effects of trust, loyalty, and reputation building. For each industry, for each platform, there can be a range of outcomes depending on internal (initial market share, consumer loyalty, ability to weather a dip in performance for longer term improvements), and external factors (industry benchmarks, consumer price expectations and sensitivity), that can allow for better outcomes from transparency decisions. Figure 14 below highlights our main contributions:

Figure 14: Shows some of the contributions of the System Dynamics model we have explored.



Where previous models of platform price transparency have mainly focused on finding analytical solutions, we have relaxed the assumptions and used simulation to explore the complex dynamics that arise when multiple platforms compete for multiple complementors and consumers.

Our results highlight the dynamic nature of developing consumer loyalty and reputation. Establishing trust and building loyalty with consumers is a process that takes time and cannot be achieved instantaneously. Additionally, it is critically important to note that this trust can also diminish over time if not consistently nurtured. Even more crucially, trust can be lost very quickly, and the effects can be deleterious, as customers will not return to platforms that have lost their trust. Brand loyalty, reputation, and consumer trust are subject to the phenomenon of "worse before better" dynamics, where there may be initial setbacks or challenges before experiencing long-term benefits (Repenning and Sterman, 2001).

As we have shown, when undertaking pricing transparency decisions, it is critical to understand not just the equilibrium states, but the transients. Additionally, our work shows that in the context of managerial decision-making, it is crucial for managers to have a sufficiently long-time horizon in their mental models. Without a long-term perspective, managers may be tempted to abandon transparency efforts in favor of short-term gains achieved through concealing certain information or shrouding pricing details. This trade-off arises because, in the short run, shrouding may lead to immediate financial benefits. However, such a strategy can undermine trust and reputation in the long term, hindering the development of enduring consumer loyalty. Therefore, managers need to consider the potential consequences of prioritizing short-term gains over the establishment and maintenance of transparency and trust in their interactions with consumers.

Our study demonstrates that incorporating a consumer behavioral learning approach and comprehensively considering all avenues of platform value creation can lead to significant insights. Specifically, it reveals that there are specific circumstances in which price transparency emerges as a profitable strategy for platforms to adopt. By augmenting traditional models with a deeper understanding of consumer behavior and accounting for the diverse sources of value generated by platforms, this research sheds light on the conditions under which price transparency can be leveraged as a strategic advantage, ultimately contributing to the platform's profitability.

Further work in this stream will continue to explore these questions and expand our model to include differences in industry, and the possibility that consumers may differentially “blame” the complementors or the platforms when faced with shrouded prices. To provide just one example of the differences between industries, it’s clear that consumers feel differently towards hidden “service delivery fees” on *Ticketmaster* (where the platform takes the blame for the hidden fees) versus hidden “cleaning fees” on *AirBnB* where the consumer may blame the hosts directly. Other interesting potential avenues to explore include ride hailing platforms, where shrouding can occur not just in the pricing, but also in the wait time, thus making it hard for consumers to compare across platform competitors.

Overall, given the ubiquitous rise of matching platforms, we believe it is critical to fully explore and understand their incentives for transparency or obfuscation. Understanding why lock-in can occur in different industries is worthwhile avenue for additional research.

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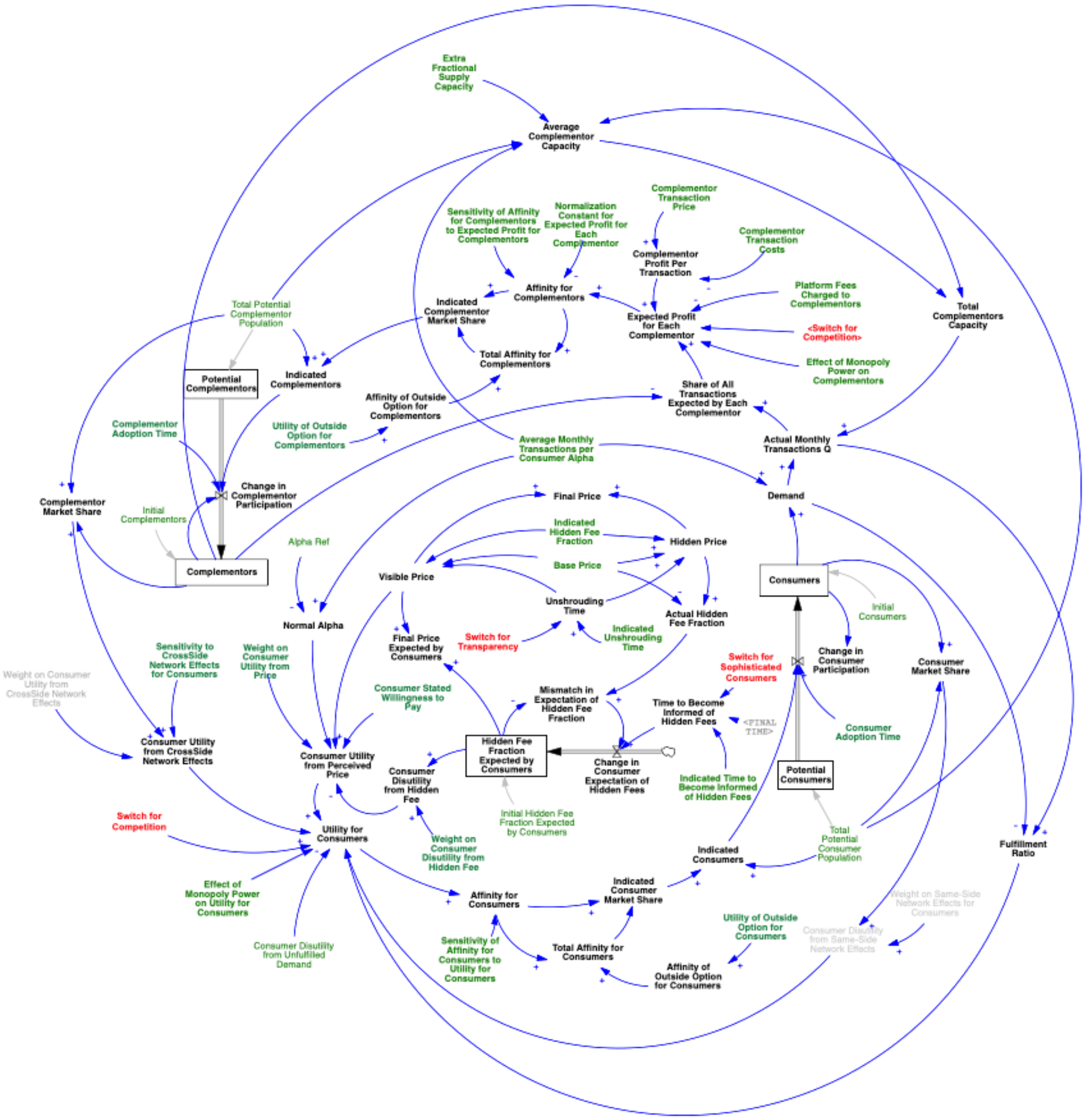
Appendix A
Vensim Model



Appendix B.
Model Equations

Actual Hidden Fee Fraction[Platforms]=
Hidden Price[Platforms]/Indicated Price[Platforms]
Units: Dmnl
The Actual Hidden Fee Fraction is the part of the Total Price that is initially shrouded from consumers. When a platform is shrouds (Switch to Transparency = 0), the Actual Hidden Fee Fraction is the same as the Indicated Hidden Fee Fraction. When a platform decides to become transparent, the Actual Hidden Fee Fraction is 0.

Actual Monthly Transactions Q[Platforms]=
MIN(Demand[Platforms], Total Complementors Capacity[Platforms])
Units: Transaction/Month
The Actual Monthly Transactions (Q), is the minimum of the Demand, and the Total Complementors Capacity. Thus, if the Demand is higher than the Capacity, the actual transactions on the platform are limited by capacity.

Affinity for Complementors[Platforms]=
EXP(Sensitivity of Affinity for Complementors to Expected Profit for Complementors
*(Expected Profit for Each Complementor
[Platforms]/Normalization Constant for Expected Profit for Each Complementor
))
Units: Dmnl
The Affinity for Complementors captures the effects of the Expected Profit for Complementors, above a threshold for the network effects. The Sensitivity parameter controls the strength of the effect.

Affinity for Consumers[Platforms]=
EXP(Sensitivity of Affinity for Consumers to Utility for Consumers*Utility for Consumers
[Platforms])
Units: Dmnl
The Affinity for Complementors captures the effects of the Utility for Complementors. The Sensitivity parameter controls the strength of the effect.

Affinity of Outside Option for Complementors=
EXP(Utility of Outside Option for Complementors)
Units: Dmnl

Affinity of Outside Option for Consumers=
EXP(Utility of Outside Option for Consumers)
Units: Dmnl

Alpha Ref=
1
Units: Transaction/(Month*People)
A reference value for the number of Transactions per month carried out by the adopters of each platform.

Average Complementor Capacity=

Total Potential Consumer Population*Average Monthly Transactions per Consumer Alpha
*(1+Extra Fractional Supply Capacity)/Total Potential Complementor Population
Units: Transaction/(Month*People)

Average Monthly Transactions per Consumer Alpha=
1
Units: Transaction/(Month*People) [0,10,0.1]
The Average Monthly Transactions per Consumer (Alpha) is the average transactions per month that each consumer makes on the platform they adopt.

Change in Complementor Participation[Platforms]=
(Indicated Complementors[Platforms] - Complementors[Platforms]) / Complementor Adoption Time
Units: People/Month
The Change in Complementor Participation is the adoption/de-adoption rate on the platform. This flow allows the actual number of Complementors participating on each platform to reach the number of Indicated Complementors.

Change in Consumer Expectation of Hidden Fees[Platforms]=
Mismatch in Expectation of Hidden Fee Fraction[Platforms]/(Time to Become Informed of Hidden Fees
)
Units: Dmnl/Month
Consumers have expectations of Hidden Fees based on prior experience. These adjust with a delay.

Change in Consumer Participation[Platforms]=
(Indicated Consumers[Platforms] - Consumers[Platforms])/ Consumer Adoption Time
Units: People/Month
The Change in Consumer Participation is the adoption/de-adoption rate on the platform. This flow allows the actual number of Consumers participating on each platform to reach the number of Indicated Consumers.

Complementor Adoption Time=
3
Units: Month [0.1,12,1]
The Complementor Adoption Time is the time it takes for complementors to join or leave the platform.

Complementor Market Share[Platforms]=
Complementors[Platforms]/Total Potential Complementor Population
Units: Dmnl
The Complementor Market Share for each platform is the ratio given by the number of Complementors that have adopted the platform to the Total Potential Complementor Population. It is a fraction between 0 and 1.

Complementor Profit Per Transaction[Platforms]=
Complementor Transaction Price[Platforms]-Complementor Transaction Costs[Platforms
]
Units: Dollars/Transaction
The Complementor Profit Per Transaction is the Complementor Transaction Price less the Complementor Transaction Costs.

Complementor Transaction Costs[Platforms]=

0.1
Units: Dollars/Transaction
Complementor Transaction Costs are the expenses incurred by the
Complementors (sellers) in their contributions to the platform.

Complementor Transaction Price[Platforms]=
0.8
Units: Dollars/Transaction
The Complementor Transaction Price is the dollar amount that
receive from the platform for each transaction.

Complementors[Platforms]= INTEG (
Change in Complementor Participation[Platforms],
Initial Complementors[Platforms])
Units: People
The number of Complementors on the platform. This is the
"Supply" side. Also sometimes called the "Sellers". If the
number of complementors is normalized to 1, this is equivalent
to the platform's share of the complementor (seller) market.

Consumer Adoption Time=
3
Units: Month [0.1,12,1]
The Consumer Adoption Time is the time it takes for
complementors to join or leave the platform.

Consumer Disutility from Hidden Fee[Platforms]=
Weight on Consumer Disutility from Hidden Fee*(Hidden Fee Fraction Expected by Consumers
[Platforms])
Units: Dmnl
The Consumer Disutility from Hidden Fee is the negative value
that consumers assign to platforms that shroud prices. It is
proportional to the Hidden Fee Fraction that consumers expect.

"Consumer Disutility from Same-Side Network Effects"[Platforms]=
"Weight on Same-Side Network Effects for Consumers"*Consumer Market Share[
Platforms]
Units: Dmnl
This is the negative utility that competition between consumers
creates for each consumer.

Consumer Disutility from Unfulfilled Demand=
0.5
Units: Dmnl [0,10,0.1]
The Consumer Disutility from the Imbalance of Supply and Demand
is the disutility incurred by those consumers that wished to
transact on the platform and that are not served because of a
limiting capacity constraint.

Consumer Market Share[Platforms]=
Consumers[Platforms]/Total Potential Consumer Population
Units: Dmnl
The Consumer Market Share for each platform is the ratio given
by the number of Consumers that have adopted the platform to the
Total Potential Consumer Population. It is a fraction between 0
and 1.

Consumer Stated Willingness to Pay=
1.1
Units: Dollars/Transaction [1,1.4,0.1]
This is the consumer's originally stated reservation price.
Hidden fees can induce the consumers to pay above this.

Consumer Utility from CrossSide Network Effects[Platforms]=
Weight on Consumer Utility from CrossSide Network Effects*(Complementor Market Share [Platforms]^Sensitivity to CrossSide Network Effects for Consumers)
Units: Dmnl
The Consumer Utility from Cross-Side Network Effects is the utility derived from one additional complementor on the platform. The formulation considers diminishing returns.

Consumer Utility from Perceived Price[Platforms]=
Weight on Consumer Utility from Price * Normal Alpha* (((Consumer Stated Willingness to Pay -Visible Price[Platforms])/Consumer Stated Willingness to Pay)-Consumer Disutility from Hidden Fee [Platforms])
Units: Dmnl
This is the utility derived by consumers from their initial price perceptions. When a shrouding platform first quotes a lower visible price than the consumer's original stated willingness to pay, consumers derive utility from this perceived surplus. This is scaled by the Normal Transactions each consumer performs on the platform on average.

Consumers[Platforms]= INTEG (
Change in Consumer Participation[Platforms],
Initial Consumers[Platforms])
Units: People
The number of Consumers on the platform. This is the "Demand" side. Also sometimes called the "Buyers". If the number of consumers is normalized to 1, this is equivalent to the platform's share of the consumer (buyer) market.

Demand[Platforms]=
Average Monthly Transactions per Consumer Alpha*Consumers[Platforms]
Units: Transaction/Month
The Demand represent the Desired Average Monthly Transactions by Consumers. This is the total volume of transactions that the consumers (Demand Side) would like to buy on the platforms. It is measured in Transactions per Month.

Effect of Monopoly Power on Complementors=
-200
Units: Dollars/(Month*People)

Effect of Monopoly Power on Utility for Consumers=
-2000
Units: Dmnl

Expected Profit for Each Complementor[P1]=
Share of All Transactions Expected by Each Complementor[P1]*(Complementor Profit Per Transaction [P1]-Platform Fees Charged to Complementors
[P1])

Expected Profit for Each Complementor[P2]=
(Switch for Competition)*Share of All Transactions Expected by Each Complementor
[P2]*(Complementor Profit Per Transaction
[P2]-Platform Fees Charged to Complementors[P2])
+
(1-Switch for Competition)*(Effect of Monopoly Power on Complementors)
Units: Dollars/(Month * People)
The Expected Profit for Each Complementor is the Share of All Transactions Expected by Each Complementor, multiplied by the Complementor Profit Per Transaction. If there is no platform competition (Switch for Competition = 0), then the Expected Profit for Each Complementor on P2 is set to a large negative value, that effectively makes it unattractive for any complementors to join P2.

Extra Fractional Supply Capacity=
0.2
Units: Dmnl

Final Price[Platforms]=
Visible Price[Platforms]+Hidden Price[Platforms]
Units: Dollars/Transaction
The Final Price that the Platform charges consumers is the sum of the Visible Price (first quote) and the Actual Hidden Fee.

Final Price Expected by Consumers[Platforms]=
Visible Price[Platforms]*(1+Hidden Fee Fraction Expected by Consumers[Platforms
])
Units: Dollars/Transaction
The Final Price Expected by Consumers is the Sum of the Visible Price and the Hidden Fee Expected by Consumers. (Currently just used for generating graphs)

FINAL TIME = 36
Units: Month
The final time for the simulation.

Fulfillment Ratio[Platforms]=
IF THEN ELSE(Demand[Platforms]=0, 0, Actual Monthly Transactions Q[Platforms
]/Demand[Platforms])
Units: Dmnl [0,1]
The Fulfillment Ratio captures the fraction of Actual Monthly Transactions to (Desired) Average Monthly Transactions Demand on the platforms. If the capacity is not a limiting constraint, the Fulfillment Ratio will be 1. If the capacity is a limiting constraint, this value will be less than 1. XIDZ(Actual Monthly Transactions Q[Platforms],Demand[Platforms],0)

Hidden Fee Fraction Expected by Consumers[Platforms]= INTEG (
Change in Consumer Expectation of Hidden Fees[Platforms],
Initial Hidden Fee Fraction Expected by Consumers)
Units: Dmnl
The Hidden Fee Fraction Expected by Consumers captures the idea that consumers learn to expect a platform's Hidden Fees, but it takes time. These price perceptions are "sticky".

Hidden Price[Platforms]=
Indicated Price[Platforms]*Indicated Hidden Fee Fraction[Platforms]*(1-STEP
(1,Unshrouding Time[Platforms]))
Units: Dollars/Transaction
The Hidden Price is the dollar amount that the platform shrouds.
The Hidden Price becomes 0 for the platform that becomes
transparent, at the Unshrouding Time.

Indicated Complementor Market Share[Platforms]=
Affinity for Complementors[Platforms]/Total Affinity for Complementors
Units: Dmnl
The Indicated Complementor Market Share between the platforms
and the outside option is split by the Logit formulation.

Indicated Complementors[Platforms]=
Indicated Complementor Market Share[Platforms] * Total Potential Complementor Population
Units: People
The number of Complementors expected by the attractiveness split.

Indicated Consumer Market Share[Platforms]=
Affinity for Consumers[Platforms]/Total Affinity for Consumers
Units: Dmnl
The Indicated Complementor Market Share between the platforms
and the outside option is split by the Logit formulation.

Indicated Consumers[Platforms]=
Indicated Consumer Market Share[Platforms] * Total Potential Consumer Population
Units: People
The number of Consumers expected by an attractivness split of
the options

Indicated Hidden Fee Fraction[Platforms]=
0.3
Units: Dmnl [0,1,0.05]
The Indicated Hidden Fee Fraction is the fraction of the Final
Price that is intially shrouding (kept hidden from consumers).

Indicated Price[Platforms]=
1
Units: Dollars/Transaction
The Indicated Price is a reference price. Set to a value of 1.

Indicated Time to Become Informed of Hidden Fees=
6
Units: Month [0.1,36,1]
The Indicated Time to Become Informed of Hidden Fees is the
average time that it takes for consumers to re-engage with the
Platform. The higher the frequency of purchases, the faster that
consumers become informed of the hidden fees they should expect
on the platform.

Indicated Unshrouding Time[P1]=
12
Indicated Unshrouding Time[P2]=
10000
Units: Month [0,36,1]

The Indicated Unshrouding Time is the time at which a platform decides to become transparent (drops the hidden fees).

Initial Complementors[Platforms]=
1
Units: People
The Initial number of Complementors on each platform. We initialize with 1 Complementor.

Initial Consumers[Platforms]=
1
Units: People
The Initial number of Consumers on each platform. We initialize with 1 Consumer.

Initial Hidden Fee Fraction Expected by Consumers=
0
Units: Dmnl
THe Initial Hidden Fee Fraction Expected by Consumers is set to 0. Consumers become informed of Hidden Fees by interacting with platforms that have Hidden Fees. (Note, an extension of the model could allow for consumers can have different expectations for the Hidden Fees to begin with.)

Mismatch in Expectation of Hidden Fee Fraction[Platforms]=
Actual Hidden Fee Fraction[Platforms]-Hidden Fee Fraction Expected by Consumers [Platforms]
Units: Dmnl
The Mismatch in Expectation of Hidden Fee Fraction captures the difference between the Actual and the Expected Hidden Fees

Normal Alpha=
Average Monthly Transactions per Consumer Alpha/Alpha Ref
Units: Dmnl
A normalized variable to capture the value of average transactions per consumer on the platform.

Normalization Constant for Expected Profit for Each Complementor=
1
Units: Dollars/(Month*People) [1,1]
The Normalization Constat for Expected Profit for Each Complementor is a scaling factor that represents the Expected Profit for Each Complementor Above which the network effects become important.

Platform Fees Charged to Complementors[Platforms]=
0, 0
Units: Dollars/Transaction
This is the fee that the Platform charges the complementors. It is not a Hidden Fee.

Potential Complementors[Platforms]= INTEG (
-Change in Complementor Participation[Platforms],
Total Potential Complementor Population)
Units: People
Potential Complementors are those that would be interested in

joining each platform.

Potential Consumers[Platforms]= INTEG (
-Change in Consumer Participation[Platforms],
Total Potential Consumer Population)
Units: People
Potential Consumers are those that would be interested in
joining each platform.

Sensitivity of Affinity for Complementors to Expected Profit for Complementors
=
1
Units: Dmnl [0,15,0.1]

Sensitivity of Affinity for Consumers to Utility for Consumers=
1
Units: Dmnl [0,15,0.1]

Sensitivity to CrossSide Network Effects for Consumers=
0.5
Units: Dmnl [0,1,0.1]
Measures the importance that Consumers give to one additional
Complementor.

Share of All Transactions Expected by Each Complementor[Platforms]=
Actual Monthly Transactions Q[Platforms]/Complementors[Platforms]
Units: Transaction/(Month*People)
The Share of All Transactions Expected by Each Complementor is
the Actual Monthly Transactions (Q) conducted on each platform,
that an individual complementor can expect. Assuming that the
complementros are undifferentiated, all complementors get an
equal share of transactions, and so the more complementors on a
specific platform, the lower the share for each individual
complementor.

Switch for Competition=
1
Units: Dmnl [0,1,1]
0 = Monopoly 1 = Competition

Switch for Sophisticated Consumers=
1
Units: Dmnl [0,1,1]
0 = Naive 1 = Sophisticated

Switch for Transparency=
1
Units: Dmnl [0,1,1]
0 = Always Shrouds 1 = Transparency

Time to Become Informed of Hidden Fees=
Indicated Time to Become Informed of Hidden Fees*(Switch for Sophisticated Consumers
)
+((1-Switch for Sophisticated Consumers)*(1000*FINAL TIME))
Units: Month [?,?,1]
The Time to Become Informed of Hidden Fees is the actual time

that it takes for consumers to become informed of the Hidden Fees on the Platform. The formulation allows for 2 types of consumers: Naive and Sophisticated Consumers. Only Sophisticated Consumers will ever become informed of the Hidden Fees. When the Switch for Sophisticated Consumers is set to 0, all consumers are uninformed (naive) and do not learn of the hidden fees - and this means that the Time to Become Informe of Hidden Fees for them is much larger than the time horizon in the model.

Total Affinity for Complementors=
SUM(Affinity for Complementors[Platforms!])+Affinity of Outside Option for Complementors
Units: Dmnl
The Total Affinity for Complementors is the sum of the Affinity for Complementors on each platform and the outside option.

Total Affinity for Consumers=
SUM(Affinity for Consumers[Platforms!])+Affinity of Outside Option for Consumers
Units: Dmnl
The Total Affinity for Consumers is the sum of the Affinity for Consumers on each platform and the outside option.

Total Complementors Capacity[Platforms]=
Complementors[Platforms]*Average Complementor Capacity
Units: Transaction/Month

Total Potential Complementor Population=
1000
Units: People [0,?]

Total Potential Consumer Population=
1000
Units: People [0,?]

Unshrouding Time[P1]=
Switch for Transparency*Indicated Unshrouding Time[P1]+(1-Switch for Transparency
)*Indicated Unshrouding Time[P2]
Unshrouding Time[P2]=
Indicated Unshrouding Time[P2]
Units: Month [0,48,1]
The Unshrouding Time depends on the Decision to become transparent. When the platform is shrouding (Switch to Transparency = 0), the Unshrouding Time is beyond the time horizon in the model. When the platform decides to become transparenty (Switch to Transparency = 1) the Unshrouding Time is the Indicated Unshrouding Time.

Utility for Consumers[P1]=
(Consumer Utility from CrossSide Network Effects[P1]-"Consumer Disutility from Same-Side Network Effects"
[P1]+Consumer Utility from Perceived Price[P1])*Fulfillment Ratio[P1]+(1-Fulfillment Ratio
[P1])*(-Consumer Disutility from Unfulfilled Demand)
Utility for Consumers[P2]=
(Switch for Competition) * (Consumer Utility from CrossSide Network Effects
[P2]-"Consumer Disutility from Same-Side Network Effects"[P2]+Consumer Utility from Perceived Price
[P2])*Fulfillment Ratio[P2]+(1-Fulfillment Ratio[P2])*(-Consumer Disutility from Unfulfilled Demand
)+ (1-Switch for Competition)*(Effect of Monopoly Power on Utility for Consumers
)

Units: Dmnl
The Utility for Consumers is the sum of it's various components. It is increasing in Consumer Utility from Cross-Side Network Effects, Consumer Utility from Perceived Price and decreasing in the Consumer Disutility from Same-Side Network Effects and the Consumer Disutility from Hidden Fees. Those Consumers that wished to transact on the platform and are not served because of capacity constraints derive a Disutility from the Imbalance of Supply and Demand. The formulation also allows for Platform Competition or Monopoly, via the Switch for Competition.

Utility of Outside Option for Complementors=
0
Units: Dmnl [-10,10,0.1]
The Utility of Outside Option for Complementors is the utility derived from not participating on any platform, and instead conducting the transactions off the platform.

Utility of Outside Option for Consumers=
0
Units: Dmnl [-10,10,0.1]
The Utility of Outside Option for Consumers is the utility derived from not participating on any platform, and instead conducting the transactions off the platform.

Visible Price[Platforms]=
Indicated Price[Platforms]*(1+STEP(Indicated Hidden Fee Fraction[Platforms
], Unshrouding Time[Platforms]))
Units: Dollars/Transaction
The Visible Price is the part of the Total Price that the platform initially shows to consumers. If the platform is not transparent, the Visible Price will differ from the Total Price by the Hidden Fee

Weight on Consumer Disutility from Hidden Fee=
2
Units: Dmnl [0,10,0.1]
Measures the importance that Consumers give to the Hidden Fee.

Weight on Consumer Utility from CrossSide Network Effects=
1
Units: Dmnl [0,5,0.1]

Weight on Consumer Utility from Price=
1
Units: Dmnl [0,10,0.1]
Measures the importance that Consumers give to the Price they Perceive on the platform.

"Weight on Same-Side Network Effects for Consumers"=
0
Units: Dmnl [0,20,0.1]
Measures the importance of one additional consumer on the platform for the Consumers.