Essays in System Dynamics for Operations Management: Policy, Platforms and Pricing

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ABSTRACT

This dissertation explores how system dynamics (SD) can improve traditional operations management (OM) models for work in public policy, understanding plaform markets, and the implications of price transparency decisions on platform firm performance and consumer behavior.

Chapter 1, co-authored with Edward Anderson and David Keith, creates a roadmap for researchers who study public policy-related OM problems. We review and organize relevant system dynamics literature in both traditional operations management, and public policy venues. We identify a set of interesting open questions and the potential SD building blocks for answering them by topic. Leveraging this review, we describe under what conditions system dynamics is most appropriate. We then identify several overarching methodological and domain gaps for future research. Finally, we propose a process for using SD with traditional OM methodologies.

Chapter 2 is joint work with Geoffrey Parker and Edward Anderson. We develop the Value Creation Lens, a framework, grounded in theory, for understanding the dynamics of platform value creation and growth. We separate a platform's value into three components: (1) the standalone value of the product, (2) the value of other participants on the platform, and (3) the value created by complementary products from 3rd party providers. We explore differences in value creation between consumer-facing and business-facing platforms, along with managerial implications.

Chapter 3 studies the effects of a common price obfuscation tactic, namely the use of shrouded hidden fees on consumer behavior and platform firm performance. I develop an SD model based on the Value Creation Lens and use it to understand the competing incentives that lead to price shrouding or transparency in online platforms. I 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 platform price transparency decisions should differ depending on market and industrial context.

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Chapter 1

Opportunities for System Dynamics Research in Operations Management for Public Policy

Operations management in the public policy context is extremely complex with many mutually interacting factors characterized by feedback loops, delays, and nonlinearities, as well as multiple stakeholders pursuing divergent objectives. Prior researchers have called for a systems approach in these contexts, arguing that standard OM methodologies such as mathematical programming, and queuing theory often cannot fully address the problems posed by complexity. In this work, we create a roadmap for researchers—both those who are familiar with systems dynamics and those who are not—for the expanded use of system dynamics to study public policy-related OM problems. We review and organize relevant system dynamics literature in both traditional operations management venues as well as public policy venues that may be less familiar to OM audiences. We then identify a set of interesting open questions and potential system dynamics building blocks for answering them by topic. Leveraging this review, we describe under what conditions system dynamics is most appropriate. We then identify several overarching methodological and domain gaps for future research. Finally, we propose a process for using system dynamics with traditional operations management methodologies.

Keywords: System Dynamics, Operations Management, Public Policy, Simulation, Scenario Planning, Literature Review

1.1 Introduction

Public policy is a fundamental driver of societal progress, and many policy-related challenges are evolving rapidly: climate and environmental concerns, healthcare, peacekeeping and security, infrastructure, and regulation of digitally enabled business models. Public policy programs are ultimately deployed through supply chains and operations where theory is put into practice. There is an obvious need to bridge public policy and operations management research and to practice it more effectively (Tang, 2016). However, this has proven difficult for a number of reasons (Sodhi and Tang, 2008). Foremost of these is that public policy problems are typically embedded in complex systems; this, in turn, makes it difficult to develop management strategies that achieve their intended results (Ackoff, 1994, Simon, 1962, Besiou and Van Wassenhove, 2015, Weick, 1989, McDaniel and Driebe, 2005). There are multiple stakeholders and decision makers with differing perspectives and often conflicting goals (Besiou et al., 2011). There are many dynamic variables that mutually interact, creating feedback loops. Significant time delays exist between cause and effect, and there are also many nonlinearities (Forrester, 1961, Sterman, 1994, Sterman, 2001). Uncertainty exists due to imperfect understanding of the problem, distorted or inaccurate information, and ambiguous legal and regulatory regimes. The resulting problem is twofold.

On one hand, standard operations management approaches typically rely on techniques that can address only a subset of these issues (Sodhi and Tang, 2008, Singhal and Singhal, 2012b, Singhal and Singhal, 2012a). On the other, while research in public policy venues captures important policy constructs, it often insufficiently models the details of operations management due to a lack of understanding of the field (Besiou and Van Wassenhove, 2015). Clearly, a high-level systems approach is needed, one that can integrate operations management issues with public policy.

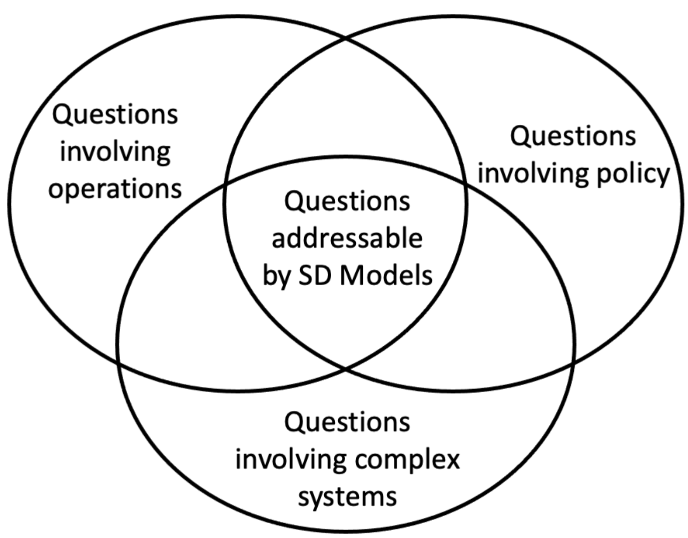
For decades, the field of System Dynamics (SD) has proven to be one such systems-level approach. SD provides a powerful lens to study operations management (OM) problems in public policy contexts (Lane et al., 2000, Besiou and Van Wassenhove, 2015, Thompson et al., 2015, Homer and Hirsch, 2006). A long history of SD-operational management interventions exist that have performed successfully in complex systems (Sterman, 2000, Van Wassenhove and Besiou, 2013, Sterman et al., 2015a, Joglekar et al., 2016, Größler et al., 2008). There are several reasons for this. SD is a computer-aided approach that originally derived from controls theory and electrical engineering (Forrester, 1961). The models themselves are generally nonlinear differential-equation state-space models, like those used in optimal control theory, albeit the models tend to be larger and require simulation. Wherever possible, variables and parameters correspond directly to real-world metrics such as "work hours per week" or "dollars per year," and many standard formulations have been developed over time (Hines, 1996). Researchers developing system dynamics models often employ techniques such as scenario planning (used in most SD operations models geared towards public policy) and group model-building among stakeholders (used less frequently in research, but often in practice). The system dynamics methodology was specifically developed to analyze dynamic problems arising in complex social, managerial, economic, and ecological systems characterized by multiple stakeholders, mutual-interacting endogenous variables, information feedback, long delays between cause and effect, and circular causality. Hence, SD an ideal tool for studying public policy problems (Besiou and Van Wassenhove, 2015). In fact, SD's first applications were in OM (Forrester, 1958). Since then, system dynamics has had a continuous thread in the OM literature, addressing topics as diverse as project management, supply chain design, process improvement, service management, and managing complementary technologies (Sterman, 1989, Sterman et al., 1997, Anderson et al., 2000, Oliva and Sterman, 2001, Akkermans and van Helden, 2002, Anderson and Parker, 2002, Joglekar and Ford, 2005). However, despite the demonstrated potential of SD, relatively few publications address OM in the public policy space. One reason for this is the number of SD papers published in the entire corpus of operations management is relatively small. (Using the methodology described in Section 3, we identified only approximately 65 papers published since 2000 in the 7 OM journals we searched.) Also, many important SD studies in this area have been targeted towards either domain-specific public policy outlets that may be unfamiliar to the OM audience or the *System Dynamics Review*.

The goal of this work is to begin rectifying this problem by providing a roadmap for OM researchers to use of SD in public policy contexts, including both those who have done SD research in the past and those who are less familiar with the methodology. To this end, we develop a "scoping review" of SD research addressing OM problems in the policy space. Scoping reviews are literature reviews that inductively examine how research is conducted in a particular field or topic, identify key characteristics related to a concept, and identify knowledge gaps and are often precursors to systematic reviews. Their purpose is to exhaustively catalog a topic using a repeatable methodology (Arksey and O'Malley, 2005, Munn et al., 2018). This paper is in the same vein as, and builds upon, Krishnan and Ulrich's (2001) review of new product development, Anderson and Parker's (2013) review of integrating knowledge work across supply chains, Joglekar et al.'s (2016) review of industry studies and public policy, and Parker et al.'s (2019) review of energy-related operations management. However, this paper necessarily differs from those prior surveys because, rather than providing a roadmap for *the study of a particular domain*, we seek to provide a roadmap for researchers *using a particular methodology in a domain*. To that end, we begin by describing why, how, and when SD might prove a useful tool for researching OM in public policy based on prior researchers' work in this area (Homer and Hirsch, 2006, Größler et al., 2008, Besiou et al., 2011, Sterman et al., 2015b, Besiou and Van Wassenhove, 2021), as well as the authors' combined 50 years of research experience in system dynamics and operations management. We then map the relevant prior literature in a structured manner by selecting a sample of approximately 150 SD papers that investigate operation managements in a public policy context. Parker et al. (2019) is especially relevant, because the authors needed to look outside the typical operations management journals. We follow them by reviewing policy-related system dynamics operations literature in both the standard operations management venues and public policy venues. We also follow Parker et al. because this review will not be exhaustive; some of the methodologies used necessarily involve judgement by the authors, such as the "KJ" clustering technique (Kawakita, 1975, Shiba et al., 1993, Burchill and Fine, 1997, Scupin, 1997), meaning the process for selecting papers and clustering them into themes is not necessarily repeatable. However, that is not our goal for generating the sample. Rather, we seek to generate sufficient coverage and insights for future researchers to build upon, per other scoping reviews. We then use the resulting literature map to identify useful exemplars of research in each cluster, along with open or sparsely researched questions in each cluster. Finally, we distill these to identify the overarching questions of greatest opportunity. Some are domain questions that emerge as common among all clusters, while others address methodology.

The closest papers to ours treat SD and complex systems in socially responsible operations (Van Wassenhove and Besiou, 2013, Besiou and Van Wassenhove, 2015). We build on them by: (1) performing a detailed scoping review, (2) expanding beyond humanitarian operations and sustainability to other policy realms, (3) including references and exemplars after 2015, and (4) identifying specific open questions in the SD literature that require additional research. Homer and Hirsch (2006) and Lane et al. (2000) also have excellent reviews, although they focus exclusively on healthcare and require updating similarly. Also related are the reviews of Größler et al. (2008) and Sterman et al. (2015b) on the use of SD for operations management. However, we focus strictly on public policy, which brings specific issues into play that are not addressed by those papers, and as a result, the roadmap for research is different. One example is the need to integrate structures drawn from political science and public policy economics. We also include more recent references.

To support these specific goals, we exclude operations management literature that does not involve SD from our sample, as well as SD research that does not involve operations management. We include only those papers that both are within the intersection of these two domains and address public policy (see Figure 1.1, below). Also, we deliberately do not address how SD models are built, validated, or tested. There are a number of excellent texts on this topic, such as Sterman (2000) and Ford (1999), and exemplar papers such as Oliva and Sterman (2001), Besiou et al. (2014), and Kapmeier and Goncalves (2018).

Figure 1.1: Questions Addressable by System Dynamics Models



Based on our work developing the roadmap above, we highlight seven gaps in the research that should be addressed to enable better use of SD for OM problems in public policy contexts. To the best of our knowledge, five of these have not been explicitly called out before, and we believe that articulating them will help other researchers. With respect to operations management problems in public policy contexts, more research effort is needed:

1. Building consensus among stakeholders with SD models.
2. Integrate SD with traditional OM methods, such as mathematical programming or queuing theory, to create hybridized methods that combine the different strengths of both approaches. Besiou and Van Wassenhove (2015) identified this as crucial, but the literature is lacking.
3. Pay more explicit attention to identifying trajectories from the current situation to a desired "ideal" state, including whether OM strategies will need to evolve over time. In particular, research must account for path dependencies that might prevent the ideal state from being achieved.
4. Feed back the results of implementation to adjust models and operations to improve future outcomes. Research in this area appears to be almost entirely lacking.
5. "Spillovers" among research silos in public policy (e.g., humanitarian operations often result from famine created by civil conflict. Sustainable OM, energy and transportation are also closely linked).
6. Create global supply chains that are more resilient to disruptions from pandemics, trade disputes, etc., and other shocks. Here the literature is sparse, aside from research directly related to medical products and services.

Based on the above points, we also propose that:

7. Besiou and Van Wassenhove's (2015) framework for using SD for OM in public policy contexts should be extended to include: consensus-building models, scenario planning, feedback from implementation outcomes, and multiple levels of SD models. Specifically, there should be simpler models for building initial consensus among stakeholders and detailed operations-planning models for interventions.

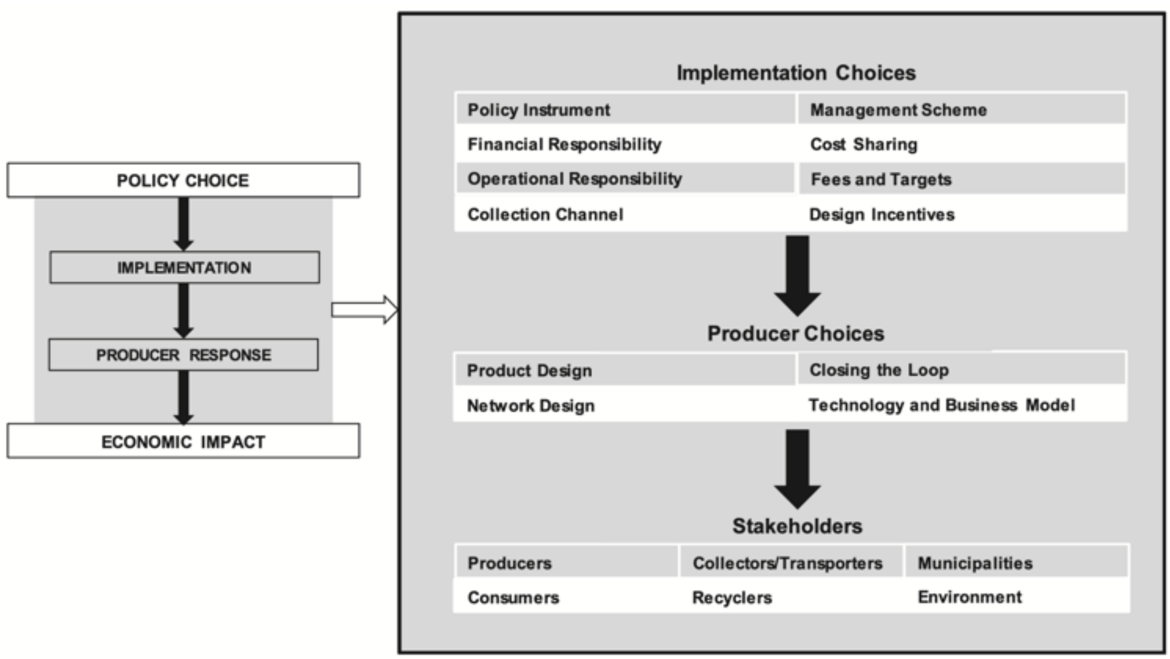
The remainder of the paper is organized as follows. First, we discuss the advantages of SD, when it is best used by OM researchers to supplement classic techniques, and the challenges to doing so. To illustrate our work, we leverage an in-depth example: developing a network of fast-charging stations for electric vehicles. We then describe the methodology used to select the article sample and cluster them into domain areas. Next, we present each identified domain as a separate section describing extant research. For each domain, we also identify exemplar papers, important open or under-researched questions, and SD building blocks for future research. We conclude with a discussion identifying overarching questions, detailing the proposed implementation process, and summarizing exemplars to provide building blocks for future research.

1.2 Features of System Dynamics Modeling

Before going further, we define some terms and abbreviations to facilitate the remainder of the paper. Unless otherwise specified or obvious from context, we follow many others in referring to public policy as simply "policy" (Joglekar et al., 2016, Parker et al., 2019). This is notably distinct from the use of "policy" in operations management when describing a decision rule (e.g., "inventory management policy"). As mentioned above, we use the abbreviation SD for S*ystem Dynamics*. We also use the abbreviation OMPP to denote *operations management in public policy contexts*.

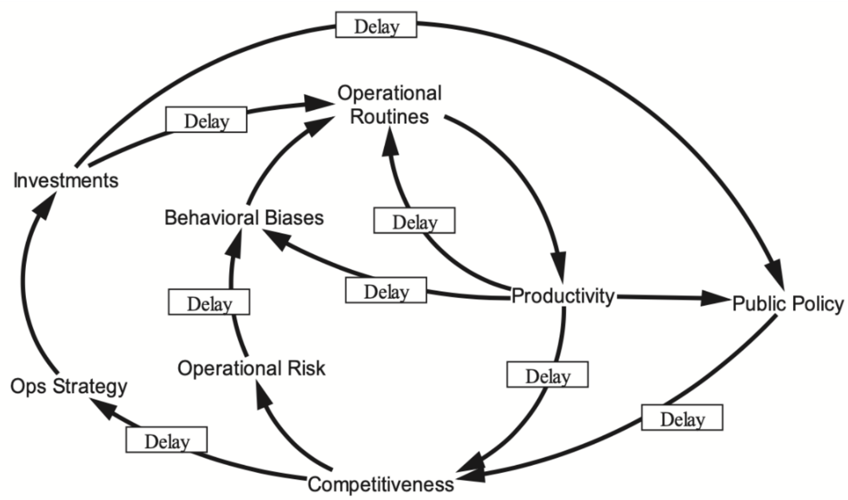
We build on Atasu and Van Wassenhove (2012), in which the authors argue that operations management problems in the public policy space are especially challenging because OM and policy decisions cannot be isolated from each other (see Figure 1.2 below). Additionally, they argue, these contexts have multiple stakeholders.

Figure 1.2: Atasu and Van Wassenhove's "Gray Zone"



Joglekar et al. (2016) expanded on this to explicitly argue that OM and policy influence each other bidirectionally (Figure 1.3). They present the example of the U.S. Clean Air Act of 1970, in which the federal government set a standard for the fuel emissions of cars sold, and once automakers met these standards, the government made the standards more stringent.

Figure 1.3: Joglekar et al.'s Diagram of Bidirectional Causality Between Operations and Public Policy



Once public policy is considered part of an OM problem, the result often has a number of characteristics that create a complex system (Besiou and Van Wassenhove, 2015). Complex systems are characterized by multiple stakeholders with conflicting objectives, context uncertainty and problem ambiguity, multiple feedbacks that mutually interact often in nonlinear ways, and endogeneity—generally with delays, constraints, and path dependency (Ackoff, 1994, Sterman, 1994, Atasu and Van Wassenhove, 2012, Joglekar et al., 2016, Besiou and Van Wassenhove, 2021). Due to these factors, potential interventions can be difficult to validate; among other reasons, interventions often result in counterintuitive behavior that is difficult to understand without a systems approach (Weick, 1989, Sterman, 1994, McDaniel and Driebe, 2005, Besiou and Van Wassenhove, 2015). Generalizability to other policy contexts is also difficult (Joglekar et al., 2016). Another issue with complex systems was nicely articulated by McDaniel (2015) who stated, "Even if I know where I am now, and where I optimally want to be, I also need to know how to get from point A to point B. On top of that, the system might be path dependent. Can I even get to point B?"

SD has a long history of successfully addressing problems in complex systems (Forrester, 1958, Forrester, 1961, Sterman, 2000, Besiou and Van Wassenhove, 2021). SD includes several features that are advantageous for studying the complex systems typical of OMPP problems. However, it also has limitations. In other words, SD is useful for some contexts, but not for others. Given this, how does an OM researcher recognize which contexts represent fruitful opportunities for employing SD?

To illustrate when and why system dynamics might be advantageous, we consider a policy problem for operations management of current import: how to expand the network of fast-charging stations in the U.S. for electric vehicles (EVs). Fast-charging stations are to electric vehicles what gasoline stations are to fuel-powered cars. The availability of fast-charging stations has been identified as the biggest barrier to EV adoption by many sources, including the U.S. Department of Energy and McKinsey & Co. (Jones et al., 2018, Gersdorf et al., 2020). Important questions include: How many stations should be built? Where should they be located? And in what sequence should they be built? These questions are part of a classic OM topic, that of facility location. In principle, we might assume this could be solved by a straightforward mathematical programming model. However, upon further examination, we see that aspects of the problem make it a complex system. Anderson et al. (2022) describes a number of these issues in detail. First, as more stations are built, more EVs will be bought, making it more profitable for new stations to enter the market (Struben and Sterman, 2008). The resulting cross-side externalities connect the two sides in a reinforcing loop, which is the hallmark of a platform (Parker et al., 2016). That said, the cross-side externalities also show diminishing returns with respect to the number of stations, creating nonlinearities. Delays are present in both the time it takes to construct stations and the time needed for consumers to perceive the improved availability of fast-charging stations and then purchase EVs in response. Also, there are multiple stakeholders, often with conflicting objectives. State and federal governments seek to expand the number of stations as quickly as possible by setting a single standard for stations that is compatible with all firms' EVs. Yet some firms (e.g., Tesla) can and have invested in their own proprietary, incompatible charging networks to maximize profits from sales of their own vehicles while excluding benefits to their competitors. Firms without their own charging networks want to enforce interoperability. Even EV owners have their own heterogenous goals. Suburban homeowners can recharge at home at night and are less sensitive to how many stations surround them than are apartment dwellers. For this reason, suburban owners are much less likely to support new taxes to fund government subsidies for building stations. Additionally, there is the technical side of the issue: How will EV driving ranges increase over time? What investments in utilities are needed to power these stations? Finally, every one of these issues—from consumer preferences to which political party is in government, to future EV range—is characterized by uncertainty. Ambiguities also exist around the problem boundary. Should the impact of mass-transit investment and ride-sharing regulation be included (Naumov et al., 2020)?

There are other issues as well, but this is enough to illustrate the complexity of what would appear at first to be a straightforward location problem.

A more detailed discussion of when an SD approach is most appropriate for addressing an OMPP problem later is presented later in this section. However, at a broad level, the EV problem illustrates these contexts. As shown by sample, SD can cope with a great deal of systems complexity because it can model a broad variety of problem contexts, decisions, and outcomes. This permits a “good” and robust solution by accounting for structures that other OM disciplines typically cannot capture. That said, it comes at a cost. SD relies on aggregating variables, and it may also miss important operational structures needed for fine-tuning solutions. Also, SD relies on computer simulation, which may result in a “good” solution that is nonetheless sub-optimal. In short, whether to use the SD methodology boils down to determining whether the system is complex enough that “good” and robust is more important than optimal and over-simplified.

Before moving on, we note that our discussion below builds on the existing body of SD work. Yet, the SD tool kit below is constantly evolving and becoming more effective (Rahmandad et al., 2015).

1.2.1 Modeling Complex Systems Structure

SD models, thanks to their systematic, rigorous computer simulations, can capture the interactions of the many industry-specific and policy-related “moving parts” needed to study OMPP problems (Joglekar et al., 2016). SD models are typically state-space differential-equation (or sometimes difference-equation) models based on the engineering discipline of control theory. Hence, SD models center on the modeling of systems with feedback loops and time delays (Forrester, 1961). As stated earlier, we do not treat how to build SD models here because many excellent references already exist (Sterman, 2000, Meadows, 2008). Fundamentally, however, there are two kinds of feedback loops. One is a “reinforcing” feedback loop in which the effect of an initial perturbation is amplified over time, for example, the accumulation of interest in a bank savings account. The other type is a “balancing” feedback loop in which an initial change is resisted, resulting in goal-seeking behavior over time, such as a hot cup of coffee cooling to room temperature. In addition, Forrester recognized that many of the relationships among variables in these loops are nonlinear, and that the interaction of these loops with nonlinearities and delays can create counterintuitive behaviors. For example, SD analysis could show that subsidies for purchasing EVs may have given early movers such a big advantage in growth and market share, they could then build proprietary station networks that ultimately hindered other competitors from entering the market (Anderson et al., 2022).

SD models include several standard formulations for decision-making behavior by both organizations and individuals, such as how employee overtime is a function of demand vs. capacity, reduced productivity of newly hired employees, and how managers forecast future demand. Other standard functions model the effect of excess inventory or backlog on management decisions. Crucially, variables and parameters are grounded in real-world metrics whenever possible, which greatly constrains the plausible values of parameters and variables. Hence, validating a model with a structure fundamentally different from reality is difficult (Barlas, 1989, Barlas, 1996, Sterman, 2000, Homer, 2012). And methods for calibrating models to data are ever improving (Eberlein, 2015, Hovmand and Chalise, 2015, Rahmandad et al., 2015).

It's important to note that this powerful modeling capability of SD does come with trade-offs relative to other commonly used OM techniques. We outline characteristics in Table 1.1 below.

Table 1.1: Characteristics of a Typical Model, for Different Modeling Techniques

	Application in OM Context	Data required	Number of Variables	Dynamic feedback	Additional Complexity	Modeling of uncertainty	Modeling of human behavior	Understanding of behavior modes within model boundaries
Game Theory	High -Level Insights (Competition/ Cooperation)	Very Low (qualitative data, if any)	Low	Yes, but rarely more than 1-3 periods	Different objective functions	Probabilistic outcomes	Rational optimizers	Very high via closed-form analytic results
Econometrics	Detailed insights (Correlation/ Causality)	High - Very High from archival and/or surveys (varies from aggregate to detailed data)	High - Very High	None (cross-sectional) Moderate (time-series)	Low	Identification strategy, clustering, residuals	Occasionally probabilistic distributions for stochastic processes.	Low - moderate due to limited ability to model counterfactuals
Optimization Models (e.g., linear programming)	Detailed operations design (particularly for capacity, Inventory, and scheduling	Moderate - Very High (Detailed structural data)	High - Very High	Depends on application. If so, linear (LPs) or multiplicative (Mixed IPs)	Low	Very Low, if any, with the exception of Inventory models, which include demand uncertainty.	None. All “physics.”	High because of algorithmic optimal policies plus detailed model structure permit counterfactuals
Dynamic & stochastic programming	Detailed operations design	Moderate (detailed structural data)	Low - Moderate	Yes. Typically, but not always, linear other than constraints	Generally low	Probability modeling for stochastic programming	Utility functions, if any	Moderate – Very High (depending on whether closed-form solutions or approximations obtain – usually related to number of variables)
Queuing Theory	Design of operations, esp. capacity planning, process, and queuing discipline design	Moderate (wait, demand & capacity, constraints)	Moderate - High	Yes. Linear Markov chains with constraints such as maximum queue size	Low	Probabilistic distributions for demand, capacity, and waiting	Only with respect to waiting (e.g., reneging, balking)	Moderate - High (depending on whether optimal closed-form solution can be found, or else, tightness of bounds)

Table 1.1: Characteristics of a Typical Model, for Different Modeling Techniques								
	Application in OM Context	**Data required**	**Number of Variables**	**Dynamic feedback**	**Additional Complexity**	**Modeling of uncertainty**	**Modeling of human behavior**	**Understanding of behavior modes within model boundaries**
System Dynamics	Consensus Building, High- or mid-level operations design	Low-Moderate from case, expert opinion, or trade journals (consensus) Moderate-High (Ops Planning) including both econometric and some structural data	Low - Moderate (Consensus), Moderate - High (Ops. Planning)	Yes. Nonlinear state-space/ compartment models	Multiple stakeholders, problem ambiguity	Generally, through sensitivity analysis for scenario planning and/or Monte Carlo analysis.	Boundedly rational (typically derived from behavioral economics of behavioral operations)	Moderate - High depending on number of variables (via numerical simulation/optimization and assuming detailed sensitivity analysis)
Agent-based modeling	Consensus Building, Mid or low-level operations design	Moderate from case, expert opinion, or trade journals (consensus) High (Ops Planning) including micro-level behavioral data of agents and structural data	Moderate-High (Consensus), High - Very High (Ops. Planning)	Yes. Nonlinear interactions of low-level agents.	Multiple stakeholders, problem ambiguity	Probabilistic distributions of individual agents' behaviors captured by Monte Carlo analysis. Sensitivity tests to probabilistic distributions and other parameters.	Boundedly rational, usually based on individual-level economic or psychological underpinnings	Moderately low – Moderately High depending on number of agents and complexity of their interactions (via Monte Carlo simulation and assuming detailed sensitivity analysis)
Discrete event simulation	Same as queuing theory	Moderate-Very High (Data needed is similar to queuing theory, but possibly also routing, demand etc. as well as entity-level characteristics)	Moderate – High (generally modeled at entity level, but generally small number of types of entities)	Yes, feedback between queues, routing, and potentially, capacity, demand and entity characteristics	Low	Probabilistic distributions for demand, capacity, waiting, routing and potentially other entity behaviors	Only with respect to waiting (e.g., reneging, balking, routing choice)	Moderate – Moderately High depending on how much more complex model is than analytic queuing models (via Monte Carlo analysis of numerical simulations assuming good ranking and selection criteria)

Traditional OM techniques drawn from Winston, W.L. 2004. *Operations research: applications and algorithms* (4th edn). Boston: Cenage. Simulation techniques from Heath, S.K., Brailsford, S.C., Buss, A. and Macal, C.M., 2011, December. Cross-paradigm simulation modeling: challenges and successes. In *Proceedings of the 2011 winter simulation conference (WSC)* (pp. 2783-2797). IEEE and Anderson, E.G., Lewis, K. and Ozer, G.T., 2018. Combining stock-and-flow, agent-based, and social network methods to model team performance. *System Dynamics Review*, *34*(4), pp.527-574.

It must be emphasized that the entries in each row represent “typical” models using a given technique; there are exceptions. For example, simplified optimization models of inventory or queues are often included as part of game-theoretic models in the OM space. Furthermore, the table illustrates some important trade-offs. One is that SD is useful for handling problems with ambiguous boundaries, such as the behavior of stakeholders, public perceptions, and domain-specific factors such as ecological, legislative, or technological processes, which a mathematical optimization model typically cannot handle. However, unlike mathematical optimization models, SD models operational structures in the aggregate rather than in detailed form, and it relies on numerical simulation. Hence, SD models can yield a robust operations solution that functions reasonably effectively over a broad range of scenarios (Joglekar et al., 2016). In another trade-off, it is more difficult to characterize the behavior of SD models than game theory models or even linear programming models, although advances in this area are being made (Oliva, 2016, Oliva, 2020). Yet another tradeoff is that SD models often need less data because they rely on a moderate number of aggregate variables. This is facilitated by modeling human beings and organizations using bounded rationality (behavioral operations management researchers may indeed consider this a plus!). However, for less complex, more straightforward systems, SD models typically deliver OM solutions that may be inferior to mathematical programming or queuing models, both of which can better leverage detailed structural data. The question then becomes how to utilize the strengths of both SD and other OM methods to get the best of both worlds. We discuss this more in Section 1.2.3, and it is a theme that recurs throughout the paper.

1.2.2 Stakeholders and Consensus Building.

Looking at Table 1.1 again highlights another point: SD models can be useful for consensus-building, something that is rarely described in our sample. The models that dominate our sample are commonly seen in the SD OM literature, being relatively large models used for operations design. Seen much less often are smaller models that serve as artifacts used to build consensus among stakeholders. Compared with the larger models, these smaller models are structurally simpler, need much less data, and can be built much more quickly while incorporating multiple stakeholders’ inputs in a process known as “group model-building” (Andersen et al., 1997, Andersen et al., 2007, Vennix, 1999). For the current purposes, stakeholders would include subject-matter experts such as ecologists and automotive engineers. This creates a powerful tool for building consensus, without which OMPP solutions often, as described earlier, fail. Once stakeholder buy-in is achieved with a simple SD model, a more detailed SD model for operations design can be pursued. However, only the latter are usually published. A good example of this is Kapmeier and Goncalves's (2018) model of island tourism sustainability. Carefully reviewing the paper, there appears to be some group model-building, but it is not stated explicitly, much less described. In our sample, descriptions of the processes by which consensus is reached is underrepresented. A related use is giving models a user interface to create "management flight simulators." This lets non-SD modelers interact easily with the model (Sterman et al., 2013). These simulators are useful for soliciting stakeholder input, helping employees and policy makers improve mental models of system behavior, and facilitating effective scenario planning.

Returning to our fast-charging station example, stakeholders include governmental agencies such as the U.S. Departments of Transportation and Energy as well as state-level equivalents. Private entities include EV firms, non-EV or traditional automotive firms, independent fast-charging station owners, battery firms, electric utilities, and technology suppliers (solar, wind, fossil, and nuclear). Finally, there are non-governmental organizations such as consumer and environmental advocacy groups. All have conflicting objectives. Perhaps more important, individual stakeholders may not fully understand what drives their counterparts, a factor that can be improved by group model-building (Andersen et al., 1997).

1.2.3 Triangulation with Other Methodologies

Once consensus is reached, another model may be used to add the level of detail needed to create practical OM solutions, possibly expanding the consensus-building SD model. While not often seen in this context, a mathematical optimization, queuing, or similar model more familiar to OM researchers is possible. However, that model would need to be tested against the higher-level SD model for robustness (Besiou and Van Wassenhove, 2015). For example, in the EV fast-charger model, the output of a high-level SD model could be used as input for allocating investment each period to specific stations using a more traditional mathematical programming facility location model. The output of the detailed model would then feed back into the high-level model to determine how the built-out network influences high-level policy variables such as station subsidies or consumer demand. Once these policy parameters are determined, the mathematical programming model would then be run again for the next period (Homer, 1999, Anderson, 2019). SD models can also facilitate closed-form analytic model development by identifying which variable relationships can be safely neglected when optimizing (Ghaffarzadegan and Larson, 2018).

1.2.4 Scenario Planning for Risk, Uncertainty, and Ambiguity

Another benefit of using SD to address public policy issues is its long history of use for scenario planning (Senge, 1990, Ringland and Schwartz, 1998). Scenario planning is useful in a policy context because many factors cannot be known with certainty, particularly over the long time horizons associated with policy, meaning participants must prepare for many plausible futures (Schwartz, 2012). SD models can facilitate this by capturing the many interacting decision variables, actors, and uncertainties typical of policy decisions, and they can also determine the range of long-term consequences of particular policies (Schwartz, 2012). Once constructed, a large parameter space can quickly be analyzed—including counterfactual scenarios—which facilitates the development of robust policies that are reasonably effective against many future eventualities (Ringland and Schwartz, 1998). Accordingly, most SD models in our sample use detailed sensitivity analysis of important parameters. A smaller number of models use formal Monte Carlo analysis (Besiou et al., 2014, Thompson et al., 2015, Kapmeier and Gonçalves, 2018). A third group copes with model ambiguity by testing the robustness of solutions against model structures or boundary changes. With respect to the EV fast-charging station example, this can be illustrated by asking: Would it be better for the government to influence station-location decisions by offering incentives to build infrastructure in rural areas not presently serviced by interstate highways? Or would it be better for the government to mandate these changes? Both alternatives might lead to so called "unintended consequences", or perverse effects on social welfare under some scenarios. Another issue is whether an EV manufacturer building fast-charging stations should be required to make its stations interoperable with cars made by other brands. Arguably, allowing firms to offer incompatible stations could expedite their investment to capture rents, at least initially. However, this could also let market leaders, such as Tesla in the U.S., lock out their competitors. This might have several effects, including reducing competition by more innovative EV-makers; hindering entry by more capable incumbents (at least in manufacturing) from the gasoline-vehicle industry; and creating fragmented or inefficient standards. All these could ultimately deter EV adoption. One could imagine that enforcing compatibility standards might be optimal, but the timing would become critical. Many parameters, such as the average driving range of new EVs manufactured five years from now, are uncertain and must be accounted for. There are also structural issues such as boundary ambiguity. For example, should new highway building projects be included endogenously, or solely as an exogenous driver? Should national restrictions on lithium exports (used to make EV batteries) be included because they may become a weapon in trade wars, particularly if EV adoption is rapid? Such structures can be drawn from the various disciplines as described in the next subsection and added into an SD model for robustness testing.

1.2.5 Bridging Disciplines

Finally, because adding additional structure to SD models is straightforward, SD models can bridge what Tang (2016) describes as "fragmented" silos in operations management, resulting in more robust strategies (Ghaffarzadegan et al., 2011, Sterman et al., 2015a). The EV fast-charging station problem goes beyond this by involving issues from disciplines outside operations management. Bhargava et al. (2021) cites not only OM articles, but also research articles from political science, economics, and domain literature from engineering. Other policy problems may of course be examined from the perspective of different disciplines but comparing them might prove valuable because their perspectives are common to many OMPP problems (Atasu and Van Wassenhove, 2012). To this end, we follow Krishnan and Ulrich's (2001) comparison of academic perspectives involved in product development (such as marketing, engineering, and operations management) by comparing these policy disciplines (Table 1.2).

Table 1.2: Comparison of Perspectives by Academic Communities Researching Public Policy
Using the Electric Vehicle Fast Charging Question as an Example

	Political Science (Sociology)	**Subject Matter Experts**	**Economics**	**Operations Management**
Perspective on Problem	A bundle of societal functions and polities' wants	Bundle of interacting "physical" phenomena needing attention	Network of macroeconomic factors including national accounts, factors of production, and monetary supplies	Set of supply chains, operational processes, and projects that create value
Typical Metrics	Public approval polls, policy compliance, citizen unrest, national security	Problem dependent (e.g., EV fleet adoption, disease mortality, etc.)	GDP gain or loss, unemployment, inflation, national accounts	Utilization, service levels, customer satisfaction measures, wait/lead times, cost
Dominant Representational Paradigm	Public welfare as a function of societal and political factors.	"Physical" models of phenomena (e.g., Climate models, Epidemiological compartment models, etc.)	Mathematical and econometric models	Value chain maps, process diagrams, project structures (e.g., critical path models, work-breakdown structures)
Example Decision Variables	Communication policies, mandates vs. incentives, centralization vs. decentralization of administration	Mandates (e.g., Lockdowns, masks, vaccine mandates; company EV mix requirements; charging compatibility standards)	Interest rates, monetary & fiscal stimuli, cost tradeoff calculations	Distribution logistics, capacity planning, facility location, sequencing of tasks
Critical Success Factors	Political legitimacy, Compliance with government mandates	Understanding of phenomena, cost/benefit ratio of interventions, quality of data	Quality of economic data, effectiveness of stimuli	Supply chain design, process design, project management processes

Each perspective lets us see part of the complex system that is building EV fast-charging stations, much like the folk tale of the five blind men exploring an elephant. One man touches the elephant's leg and says an elephant is like a tree. Another touches the elephant's tail and likens the elephant to rope, and so on. Of particular importance here are the decisions, none of which can be taken in isolation. For example, the value chain inherent in the location of fast-charging stations cannot be decided without political decisions, such as whether all stations should be mandated to be interoperable; economic decisions, such as whether to subsidize the purchase of EVs to stimulate demand; and engineering decisions, such as whether to put a new battery technology into a vehicle, which might favor range over reliability.

This structure, at an abstract level, is relevant to many other problems with only minor changes (Rahmandad et al., 2020). Hence, many papers in our sample leverage viewpoints drawn from beyond OM. For example, Table 2 could also represent the public health problem of immunizing a population to cope with a pandemic. In this case, epidemiology and physiology experts would replace engineers as the domain experts, typical metrics such as the percent of the population immunized and infected would be used, SEIR (Susceptible, Exposed, Infected, Recovered) compartmental models would be employed as the dominant representational paradigm, and so on. This could lead to decisions around fast-tracking vaccine development, prioritizing which population segments to vaccinate first, and allocating capacity (including beds, staffing, and ventilators) to hospitals in different areas (Goncalves et al., 2022)

In short, looking at the literature sample, an SD approach is most appropriate when features of an OMPP problem must be accounted for, but cannot be captured by other OM methods. Otherwise, though the solution may appear "optimal," it will not be robust enough for the problem's complexity.

1.3. Sample Selection and Methodology

Literature that applies SD to operations management in policy contexts is widely dispersed in many journals across many fields. What's more, every year the OM community publishes a large number of articles across a wide range of domains. To manage the scope of our literature search, we follow prior papers such as Krishnan and Ulrich (2001) and Parker et al. (2019). These had the same goal of identifying current research opportunities for OM scholars. That is, we do not attempt to create an exhaustive review, but rather a scoping review as described earlier, upon which contemporary scholars can build relevant research. Leveraging those prior surveys, we use the following methodology to select our sample:

1. We conduct a search for articles in the leading operations management journals: 1) *Production and Operations Management*, 2) *Manufacturing & Service Operations Management*, 3) *Journal of Operations Management,* 4) *Operations Research*, and 5) *Management Science.* (*Leading* is defined as the OM outlets appearing on a list compiled by the University of Texas, Dallas, of leading academic journals in major business disciplines. This list was retrieved on December 23, 2021, from https://jsom.utdallas.edu/the-utd-top-100-business-school-research-rankings/.) To identify relevant articles, we used the following search terms: "System Dynamics," "simulation," and "modeling." System Dynamics is a sufficiently unique key term, and we are confident that the vast majority of research using the SD methodology published in these journals has been identified. We limited our search to articles published since 2000 because our main goal is illustrating research questions for current and future researchers. We then eliminated those articles judged by the authors as either not related to public policy (i.e., they addressed only "inventory management policies") or not related to system dynamics. From a total of approximately 11,500 articles in these journals over the period of interest, our search resulted in approximately 50 articles.
2. We also searched the *System Dynamics Review* over the same period (post-2000) for research using the topics "operations management" and "policy." This is the journal of the System Dynamics Society, the association of SD researchers. In this sample, we did not include either "simulation" or "system dynamics," because in these outlets, these terms are redundant. Again, we eliminated those articles judged by the authors to be unrelated to public policy. Our search resulted in a total of approximately 25 articles.
3. Because of the paucity of articles revealed in the above searches related to OM in a public-policy context, we searched the list of SD research publications maintained by the System Dynamics Society, which contains approximately 2,500 journal articles. This list can be obtained from the System Dynamics Society's bibliography webpage (https://www.systemdynamics.org/bibliography). The System Dynamics Society Bibliography revealed that SD research also appeared frequently (as defined by over 50 instances) in two operations management-related journals: (1) *Journal of the Operational Research Society* and (2) *European Journal of Operational Research*. We added these, not only for their frequency of publications, but also their explicit linkages (unlike the six journals listed above) to research societies based outside the United States. We then searched these journals for articles using the same criteria as (1) above. From the total of approximately 9,200 articles in these journals over the period of interest, our search resulted in an additional sample of approximately 15 articles.

Because the searches described above surfaced a relatively small number of articles, we then broadened our scope in three ways:

4. We searched the System Dynamic Society's bibliography again because it had earlier proved to be an invaluable resource for searching the broad swath of journals in different policy domains. The search parameters used on the database were the same as for the *System Dynamics Review* above. This yielded approximately five articles that had not been captured by the previous searches.
5. We contacted the Jay W. Forrester Award winners from the past 20 years (i.e., since 2000), asking them to provide additional guidance on relevant articles we may have overlooked. The Forrester award is given annually for the best SD research by the System Dynamics Society. We also searched for articles by Award winners written after 2010 that treated operations management in a policy context. This yielded approximately 15 articles that had not previously been captured by the above searches.
6. We searched the articles in (1)-(5) for references to expand our review to capture influential articles useful to the contemporary researcher in OMPP following the expansion by Parker et al. (2019) of their search. This resulted in approximately 40 additional articles.

Next, we clustered the sample into research areas using the "KJ" clustering method (Graham et al., 2001, Shiba et al., 1993), which was also used in prior reviews such as Anderson and Parker (2013). The resulting clusters are: (1) humanitarian operations and crisis management; (2) healthcare operations management; (3) conflict, defense, and security; (4) transportation, logistics, and infrastructure; (5) sustainable operations; (6) new business models; and (7) energy. We use these clusters to structure our review in Section 3. Some of these research areas were similar enough to Production and Operations Management Society (POMS) colleges that we used their category names where appropriate.

1.4. Literature Review and Open Questions by Cluster

Each subsection below addresses one of the research clusters identified in Section 1.3. For each cluster, we describe the nature of the cluster using review articles, and we identify those aspects of complex systems that are particularly salient. We then identify exemplar articles of rigorous and important research in the cluster as well as other articles of interest. For each cluster, a summary table at the end of each section creates a roadmap for researchers that: (1) contains both the exemplars and other relevant articles in the sample; (2) subdivides the articles into topics for ease of reference for researchers, as well as how each topic leverages contributions from SD; and (3) includes relevant open questions and additional SD "building blocks" in the extant literature relevant to the open questions.

1.4.1 Humanitarian Operations and Crisis Management

In the last half-century, the number of disasters—whether natural (e.g., earthquakes, hurricanes, monsoons, floods, droughts), man-made (e.g., war, displacement, forced migration, famines), or pandemics—has risen dramatically. Forecasts show that in the next half-century, these events will likely become even more frequent (Allahi et al., 2018). Humanitarian operations efforts strive to provide aid and relief in contexts typical of the complex systems described earlier. Particularly problematic are situations involving multiple stakeholders with often widely differing objectives (Starr and Van Wassenhove, 2014). Additional pressures on humanitarian organizations (HOs) include inadequate funding, high staff turnover, limited time horizons in which to react, and compressed project life cycles (Besiou and Van Wassenhove, 2020). The operations management literature has proposed many excellent approaches for planning and directing humanitarian aid, and these have proven to be of great help. However, studies have also shown that other organizations have faced difficulty when implementing these approaches; hence, they have posited that research into operations in this context could often benefit from an SD approach (De Vries and Van Wassenhove, 2020).

Kunz et al. (2014) is an exemplar paper in this cluster. It uses extensive scenario and sensitivity analysis to explore the delivery process of ready-to-use therapeutic food items in the immediate response phase of a disaster. The paper then builds a model to analyze different preparedness scenarios for therapeutic food items to enable a fast response. The authors find that the fastest method is to preposition stocks of relief supplies in all countries prone to disasters. However, this approach, while fast, is also prohibitively expensive. An alternative approach involves investing in capabilities such as training staff and pre-negotiating customs and other arrangements in countries prone to disaster up front. In this way, centrally held stocks can be rapidly transferred to affected regions. Compared with other approaches, this is less costly, but also slower. The paper's authors conclude that a mix of the two strategies provides the best performance and recommend specific allocation policies for relief organizations.

Besiou et al. (2014) is another exemplar. The authors apply a similar approach to Kunz et al. but add Monte Carlo analysis to examine whether vehicle fleets for humanitarian relief should be locally purchased as needed or centrally purchased and then held in reserve. Perhaps unsurprisingly, the paper finds that a hybrid policy is generally best. However, the analysis is interesting for two reasons. First, the authors explicitly extend the dynamic programming strategies for centralized purchasing developed in Pedraza-Martinez and Van Wassenhove (2012) by adding three complexities: (1) decentralized procurement is possible; (2) relief efforts due to natural disasters may also be needed; and (3) demand for vehicles is stochastic. Second, the authors also broaden the study and span silos by studying the degradation of procurement efficiency that results when program-funding groups earmark aid to specific locations.

Other topics addressed by SD research emerged from our cluster analysis as well. One topic directly addresses the compressed “life cycle” of humanitarian operations (e.g., Ni et al., 2015). Another is humanitarian supply chains. Among these, Diaz et al. (2019) and Badakhshan et al. (2020) tie back to the original SD work of Forrester (1961) by studying the bullwhip effect in relief efforts.

One important challenge still open in the field of humanitarian operations is how to best deal with the complexity of last-mile distribution. As identified by logistics and distribution studies, the last mile accounts for most of the cost under normal day-to-day conditions, particularly in developed nations with established carrier services and good infrastructure. However, humanitarian organizations are often tasked with last-mile distribution in areas with little to no infrastructure. Related to this, extant work has used classic OM optimization approaches to plan routes, determine vehicle fleet sizes, and address coordination challenges in humanitarian relief chains (Balcik et al., 2008, 2010). Due to the complexity of the systems in which these problems are embedded, SD could prove a useful tool (De Vries and Van Wassenhove, 2020). Another challenge involves developing strategies to cope with hoarding, which is commonly seen in humanitarian operations settings. Hoarding results in longer delivery times and greater perceived shortages, and it creates feedbacks that intensify scarcity and destabilize supply chains by reinforcing the perception of shortages (Sterman and Dogan, 2015). If hoarding could be ameliorated with appropriate policies, then the difficulty inherent in rapidly establishing ad hoc supply chains during crises could be markedly reduced. Another open question is how to best manage the relationships among humanitarian operations, media presence and coverage of operations, and humanitarian organization funding (Burkart et al., 2016). Because of its complexity and overlap with marketing, this question is an ideal candidate for SD research. Nageswarakurukkal et al. (2020) begins to address this by examining how social media affects publicity, fundraising, and operational efficacy, and Keith et al. (2022) studies how management emphasis on fundraising can detract from operational effectiveness. Finally, humanitarian operations problems often spill over into other policy clusters, such as the possibility that drought and food shortages may result in civil unrest, which in turn can exacerbate food shortages (Besiou et al., 2011). This complex humanitarian topic is another excellent area for SD research, one that according to our sample, remains underexplored. Table 1.3 below organizes the roadmap for the cluster as described at the beginning of the section and provides additional references from our sample.

Table 1.2: Humanitarian Operations and Crisis Management Literature and Open Questions					
Research Topics	**Selected References**	**Useful SD Features**	**Policy Questions***	**Operational Questions***	**Relevant SD Structures for Future Research****
Literature Review	Tomasini et al. (2009), Starr and Van Wassenhove (2014), Van Wassenhove and Besiou (2013), Besiou and Van Wassenhove (2015), Allahi et al. (2018), Besiou and Van Wassenhove (2020, 2021)	Ability to include both short term and long term time horizons (Van Wassenhove and Besiou, 2013) Complex problems with multiple stakeholders and conflicting goals (Van Wassenhove and Besiou, 2013)	How to can we holistically understand the relationship of humanitarian operations with other policy challenges?	How can we apply our knowledge from traditional OM problems to maximize recipient outcomes in humanitarian relief operations?	Use and build on existing small models per Ghaffarzadegan et al. (2011) to aggregate for larger, more complex problems
Disaster Life Cycle Models and Emergency Preparedness	Cooke (2003), Deegan (2006), Ni et al. (2015), Diaz et al. (2019)	Accounts for models of managerial behavior (BD-13.1 & BD-15) Uses established models of project management (BD-2.3)	How can we find the optimal level of preparedness given economic constraints and cyclical and stochastic nature of disasters? What are the contexts of disaster relief recipients that might complicate relief delivery?	How to manage compressed relief effort/project lifecycle? How to manage complications in demand due to hoarding in a disaster area?	Behavioral Model of Hoarding (Sterman and Dogan, 2015) Extend existing models to endogenize production rates
Balancing Competing Demands in Disaster Management	Gonçalves et al. (2011), Kunz et al. (2014)	Capability Trap model of the tradeoffs between providing relief and building capacity (Gonçalves, 2011), where immediate needs are not aligned with long term goals	How to can different stakeholders coordinate to get crisis relief to affected areas quickly and efficiently?	How to manage last mile distribution in underdeveloped areas? Where do on-the-ground problems differ from those in for-profit settings?	Capability traps in non-profit fundraising (Keith et al., 2022)
Vehicles and Fleet Maintenance	Besiou et al. (2011), Pedraza-Martinez and Van Wassenhove (2012), Besiou et al. (2014), Cruz-Cantillo (2014)	Maintenance models vs customer satisfaction (BD-2.4)	How do we set up and maintain capacity to be quickly deployed in a disaster zone?	What are the effects of earmarks and other constraints from donors?	Maintenance Traps (Bivona and Montemaggiore, 2010) Media/public relations effects (Keith et al., Forthcoming)
Humanitarian Supply Chains and Logistics	Peng et al. (2014), Remida (2015), Cortés et al. (2019), Badakshan et al. (2020)	Bullwhip and oscillation models (BD-17.1) Stock management (BD-17.3)	How can we set up an efficient system to deal with the unpredictability of demand, suddenness of the disasters, and urgency of action?	How is the success of a relief operation affected by the political characteristics of the region affected? What is the effect of experience and burnout on relief worker capabilities?	"Rookie-Pro" aging chains that account for heterogeneous productivity of experienced vs inexperienced employees (BD-19.1, 19.2) Dynamics of worker burnout (Homer, 1985)

*Source of question is from authors as opposed to from research agendas in sample papers **Unless otherwise indicated, SD structures can be found in Sterman (2000), which summarizes seminal research in system dynamics, and presents many of the commonly used structures and formulations for a wide variety of modeling applications. For ease of reference, we will note the Chapter and Section where a relevant structure is presented as "BD-xxx yyy" where xxx is the chapter and yyy is the section.

1.4.2 Healthcare Operations Management

Healthcare operations management (HOM) is widely recognized as an exceedingly challenging domain, one that does not lend itself to easy solutions (Koelling and Schwandt, 2005, Dai and Tayur, 2019). In the United States, healthcare is characterized by financial waste, amounting to approximately 5% of GDP (Leape et al., 2009), numerous safety issues—such as unnecessary hospital deaths being the country's third leading cause of death (Donaldson et al., 2000)—and poor service (Binary Fountain, 2018). While not as well documented, these issues also exist in other national health systems such as Sweden (Porter and Teisberg, 2006). These issues are due in no small part to stakeholders with different goals. These include: patients; doctors, nurses, and other healthcare providers; hospitals; insurance companies; pharmaceutical manufacturers and distributors; and local and national governments. Public policy makers that try to coordinate the system have limited resources, requiring trade-offs to be made. The very complexity of the healthcare system has attracted scholars from fields as varied as operations research, engineering, economics, and medicine to propose powerful and practical solutions (Dai and Tayur, 2019, Keskinocak and Savva, 2020). That said, many innovative approaches have challenges directly related to a fragmentation of scholarship (KC et al., 2020). To address these gaps, the Professional Society for Health Economics and Outcomes Research (ISPOR) have recently stated that HOM "exhibits a level of complexity that ought to be captured using dynamic simulation modeling methods" (Diez Roux, 2011, Marshall et al., 2015). This may partly explain why this cluster has the greatest number of papers in our sample. Darabi and Hosseinichimeh (2020) document in their excellent survey of SD in health and medicine how SD has since the 1960s been successfully used to study a wide variety of topics in HOM, generally using simulation to complement empirical and observational studies. The authors often provide surprising insights into the most powerful levers to avoid policy resistance (Darabi and Hosseinichimeh, 2020). Similar observations were made by an earlier survey (Homer and Hirsch 2006).

Numerous studies have explored models for public health (e.g., Homer and Hirsch, 2006, Atkinson et al., 2015, Dangerfield, 1999, Kang et al., 2018, Newell and Siri, 2016). One outstanding example is the series of papers studying polices for polio eradication (Thompson and Tebbens, 2007, Tebbens and Thompson, 2018). Much of this is summarized in Thompson et al. (2015). It is the result of a multi-method approach, integrating SD with several other OM and research techniques, including decision analysis, game theory, linear programming, and inventory models. The series is also a model of stakeholder collaboration. Working with the Global Polio Eradication Initiative (GPEI), the researchers demonstrated that polio eradication efforts need to be continued with the utmost vigor, even as polio is brought under control. Much like a banked fire that, if disturbed, throws off embers that ignite other fires, even a small number of polio cases can flare up quickly into larger outbreaks. A quick response is paramount, even if that comes at the cost of imperfect coverage. Hence, a large stockpile of vaccine needs to be maintained at all times. The paper also develops a policy to determine the optimal timing for a switch from an oral poliovirus vaccine to an inactivated poliovirus vaccine. While the oral poliovirus vaccine is cheap and effective for snuffing out an outbreak quickly, it can (very rarely) cause dangerous side effects—or worse, mutate to create a dangerous polio epidemic of its own.

One topic area where SD has been widely adopted at a more micro level is models of disease in the human body. Estimates show that nearly half of all U.S. adults suffer from at least one chronic illness, and that these illnesses ultimately result in seven out of 10 deaths (Centers for Disease Control & Prevention [CDC] 2015). This highlights the need for new tools to determine the most effective interventions for specific illnesses. Chief among these chronic illnesses are obesity, diabetes, and heart disease. Kang et al. (2018) develop a model that incorporates goal programming to help support decision making and intervention planning at different phases of chronic kidney diseases (CKD) management. Other SD research in this area addresses mental health issues, including depression in teenagers (Hosseinichimeh et al., 2018) and Post-Traumatic Stress Disorder (PTSD) among military personnel and veterans (Ghaffarzadegan et al., 2016). The latter is an exemplar of scenario planning in an SD environment. It is also an exemplar of a commonality discussed in much SD research, namely, that investing beforehand is far more effective than providing treatment afterwards. In particular, the authors found that programs to create resiliency (in this case, the ability to rapidly recover from traumatic effects) before a combat assignment are more cost-effective than screening or treatment afterwards.

SD models have also been prominent in epidemiology, going back to traditional Susceptible, Infected (SI) models for HIV transmission (Roberts and Dangerfield, 1990, Dangerfield et al., 2001). More recently, researchers have developed SEIR (Susceptible, Infected, Exposed, Recovered) models that also include behavioral responses such as social distancing and self-isolation, as well as endogenously considering increases in hospital capacity in response to the current global COVID-19 pandemic (Struben, 2020, Ghaffarzadegan and Rahmandad, 2020). Rigorous formulations and novel approaches have also shed light on how to best estimate parameters for global epidemics as they are unfolding, allowing for more confident and robust models, even in the face of limited and inconsistent data (Rahmandad et al., 2020). Betcheva et al. (2020) describe an intervention to build a similar model with UK National Health Service planners and adds the mental health sector.

SD modeling has also been used successfully to study patient flows and capacity planning in healthcare institutions (Diaz et al., 2015, Wang et al., 2015). For an example of studying patient flows and capacity planning, Lane et al. (2001b) explore the relationship between a reduction in hospital capacity by the UK's National Health Service (as measured in bed reductions) and emergency room waiting times. By combining sensitivity with extensive scenario testing of a calibrated SD model, the authors found that, counter to conventional wisdom, the major impact of bed shortages is most directly felt not in emergency admissions, but instead in elective admissions. Hence, the traditional practice of using emergency room waiting times to measure the effect of bed reductions can be misleading. This paper, though relatively old, remains an exemplar for three other reasons. One, it offers an extended description of SD validation tests used on the model. Two, the paper describes (if briefly) how the model was developed via group model building techniques—and ultimately accepted as valid—among stakeholders. Three, it provides an excellent discussion of the tradeoffs between modeling with SD and discrete event simulation.

As patient tracking information continues to grow, the interconnectedness of the healthcare system has become of increasing interest to scholars. Some have broadened the boundary of the systems they study to include pricing and supply chain interactions between the pharmaceuticals and insurance industries (Paich et al., 2011, Kunc and Kazakov, 2018, Li et al., 2014, Darabi and Hosseinichimeh, 2020). By studying the interactions among healthcare providers, payers, and patients, they also highlight how misaligned incentives among these groups may lead to rising costs and lower service levels. In addition, Azghandi et al. (2018) addresses the complication of recalls and reverse logistics. Other papers in this stream focus on product development and market entry on healthcare operations such as marketing and strategy variables (Paich et al., 2011). Kunc and Kazakov (2018) is an exemplar because it describes how they developed a model and turned it into a flight simulator to make a decision-support tool, which was used in a workshop for multiple stakeholders.

Finally, the treatment by Goncalves et al. (2021) of capacity serves is an exemplar for a number of reasons, including excellent sensitivity testing and calibration. Perhaps even more important, this paper provides one of the best descriptions of how consensus is created by stakeholders using system dynamics. Interestingly, it also offers a paradigm that differs from those provided in prior research (Vennix, 1999, Andersen et al., 1997.)

Our survey of the literature has identified several open questions relating to the interaction of actors, costs, and quality of service that are explored below. Dai and Tayur (2019) argue that the huge cost issues facing policy makers are not just a question of misaligned incentives, but also the result of perverse incentives among providers, physicians, pharmaceutical companies, insurance companies, and many other actors that drive unintended cost increases. Further, the dynamic complexities of these relationships inhibit process improvement and result in the characteristic “fixes that fail.” For example, it is widely acknowledged that pharmaceutical companies increase prices whenever possible to offset their high R&D costs. Despite public outcry, pharmaceutical companies continue to enjoy historically high margins, averaging close to 70% gross margins and 25% net margins (Sood et al., 2017). Pharmaceutical companies are aware of the controversies surrounding their pricing strategies, and some have taken steps to improve their public perception (Dai and Tayur, 2019). Compounding the problem is the fact that healthcare pricing is generally opaque and case-specific, so that patients are not generally able to make informed decisions, instead relying on the recommendations of their networks or physicians. This is typical of many problems in healthcare. A final complication is caused by remuneration policies. Arguments have been made that paying a fee for each service increases unnecessary procedures, leading to the implementation of either a fixed-fee for a given diagnoses (“bundled payments”) or payments to institutions based purely on the population in their catchment areas (“accountable care organizations”). Clearly, SD studies could be of great help in researching these problems and guiding future policy decisions. However, the SD literature in the pharmaceutical market dynamics space is sparse. To the best of our knowledge, the only major research paper in this space is by Paich et al. (2011). Many more papers are needed.

Another important open challenge for policy makers is the need to improve quality and safety. Multiple studies have found evidence that, despite increasing costs, healthcare is not as safe as it should be. It is estimated that approximately 300,000 preventable deaths per year occur as a result of medical errors, and over $50 billion per year in costs (including lost income, lost disability, and healthcare costs) for these adverse events, 60% of which may have been preventable (Donaldson et al., 2000, Leape et al., 2009). What policies could be put in place to curb these? Part of the problem is that process improvement is difficult to implement because of the severe penalties assessed on caregivers who have made mistakes. The unintended consequence is that mistakes are underreported (Norman, 2013), obscuring data that could be used to create safer processes. This behavioral feedback loop makes this topic particularly amenable to SD research.

Studies have found that the United States wastes close to half a trillion dollars annually on reducing healthcare waste (Hopp and Lovejoy, 2012). Leape (2002) cites duplicated tests and procedures as the second greatest driver of healthcare waste. This is partly due to fragmented information systems, resulting in one institution being unable to see what another institution has already done with a patient. At a higher level, waste is also created by the reimbursement policies of insurers, including national health systems. For example, payments to hospitals at a per capita rate, based on the number of patients served, may lead to skimping on acute, needed healthcare. Alternately, fee-for-service can induce skimping on preventive care. This particularly affects disadvantaged groups with fewer means of payment, or insurance. Another issue is remuneration for penalties on patients being readmitted within 30 days by U.S. Medicare, which has led to mixed results. This follows from the existing pressure on hospitals to shorten patient stays during initial treatments, perhaps leading hospitals to release patients too early in some cases. All these issues call out for SD research.

Both duplicated treatments and patient safety should be improved by Electronic Healthcare Records (EHR) systems, at least in principle. That is why the United States incentivized the installation of EHRs by all healthcare institutions under the country's Affordable Care Act. However, unintended results ensued. At the time the policy was implemented, the easiest-to-install systems were also the most difficult to integrate. This led to systems at different institutions being unable to communicate with each other, obviating some of the desired safety and cost improvements. Complicating this issue, government regulation of compatibility standards remains weak. As a result, this incompatible healthcare data ultimately confers a "winner-takes-all" advantage for those healthcare information systems vendors with the largest installed bases.

Other open questions that require urgent attention have been brought to the forefront by the COVID-19 pandemic, which laid bare the inability of many governments to deal with pandemics and other public health crises at both the operational and policy levels. For example, one shortcoming has arisen as a result of the business practice, over the last few decades, of relentlessly pursuing supply-chain efficiencies by reducing inventories and safety stock levels and instead implementing just-in-time delivery systems. This was fine when conditions were predictable, but in the face of supply shocks from the shutdown of China and later Mexico, this efficiency came at the cost of robustness. Stockouts cascaded through the supply chain, creating critical shortages of personal protective equipment (PPE), testing supplies and equipment, pharmaceuticals, and materials necessary to produce vaccines (McMahon et al., 2020). Hoarding, as discussed earlier, complicated the situation. Even more critically, both local and national governments worldwide have struggled to communicate clear policies and manage adherence fatigue. While there is some SD research on managing these issues, more is needed to provide valuable insights. For example, SEIR models have been developed to both illustrate the spread of COVID-19 and account for more behavioral responses such as public self-isolation measures when the death rate is high (Struben, 2020, Fiddaman, 2020, Rahmandad et al., 2020). Other studies have also included increased hospital capacity (Goncalves et al., 2021) and inventory trading between countries (Van Oorschot et al., 2022). However, few if any of these studies have linked the contagion model to the economic model to study linkages between the two. Moreover, COVID-19, as well as other recent epidemics such as Ebola, have revealed the necessity of studying project management in the specialized and heavily regulated context of accelerating vaccine and pharmaceutical development during a pandemic. While building the supply chain to bring parts and raw materials to manufacture the vaccine kits would be difficult under any circumstances, it is currently complicated by shortages due to bullwhip effects. Then there is the distribution of the vaccines. As discussed in the section on humanitarian operations later in the paper, this is also a complex problem. For example, in some areas, the last-mile problem might very well include delivery by donkeys carrying vaccines that require refrigeration or freezing (Kaplan, 2020). The need for SD-based research into how this is to be done is urgent.

Clearly, as the field continues to grow, there will be ample opportunities to continue leveraging the strengths of SD modeling for HOM research. Table 1.4 below organizes the roadmap for the cluster as described at the beginning of this section and provides additional references from our sample.

Table 1.3: Healthcare Operations Management Literature and Open Questions

Research Topics	Selected References	Useful SD Features	Policy Questions*	Operational Questions*	Relevant SD Key Structures for Future Research**
Literature Review	Luke and Stamatakis (2012), Darabi and Hosseinichimeh (2020)	Complex problems with multiple stakeholders and conflicting goals (Darabi and Hosseinichimeh, 2020)	What can we learn from modeling in relation to diseases and disease-spread, organizational and healthcare delivery structures, and how can it be adapted to different regions?	How can we improve quality and consistency in healthcare delivery, while reducing costs and increasing coverage?	Use and build on existing small models per Ghaffarzadegan et al. (2011) to aggregate for larger, more complex problems
Models for Public Health	Taylor and Dangerfield (2005), Homer and Hirsch (2006), Mustafee et al. (2010), Homer and Curry (2011), Katsaliaki and Mustafee (2011), Atkinson et al. (2015), Marshall et al. (2015), Newell and Siri (2016), Betcheva et al. (2020), Van Oorschot, (2021), Goncalves (2021)	Accounts for models of managerial behavior (BD-13.1 & BD-15) Uses established models of project management (BD-2.3)	How should the interactions between healthcare stakeholders be designed to reduce costs? How do we reduce inequity in patient outcomes for the disadvantaged?	How can information systems be better designed to support processes and healthcare supply chains? How can process improvement in safety be addressed in a system that blames individuals rather than processes?	Dynamics of worker burnout (Homer, 1985), corner cutting and overtime (Oliva and Sterman, 2001). Also summarized in BD-14.
Epidemiology	Roberts and Dangerfield (1990), Dangerfield (1999), Dangerfield et al. (2001), Ghaffarzadegan and Rahmandad (2020), Fiddaman (2020), Rahmandad et al. (2020), Struben (2020)	Endogenous response to risk perceptions	What policies improve treatment quality, consistency and safety overall?	How can we be better prepared for outbreaks? How do we make supply chains more robust during pandemics?	SEIR models, extended to include quarantines, vaccinations, distancing mandates, adherence fatigue, and behavioral risk perceptions.
Effectiveness of Interventions	Tengs et al. (2001), Ahmad and Billimek (2005), Kang et al. (2018), Jalali et al. (2019)	Dynamics of communication, motivation and erosion, impact adoption and implementation (BD-1.1)	How can waste be removed from current processes?	How can we improve project management for crashed programs? How can supply chains be erected quickly?	Temporal trade-offs or “Capability Traps” (Repenning and Sterman, 2002)

Table 1.3: Healthcare Operations Management Literature and Open Questions					
Research Topics	**Selected References**	**Useful SD Features**	**Policy Questions***	**Operational Questions***	**Relevant SD Key Structures for Future Research****
Patient Flows and Capacity Planning	Van Ackere and Smith (1999), Lane et al. (2000, 2001a), Smith and Van Ackere (2002), Diaz et al. (2012), Wang et al. (2015), Lane and Husemann (2018)	Modeling queues, and the interaction of delays and bottlenecks (BD-11.2)	How can specific drivers, such as payment structures, be redesigned to reduce excessive or duplicated services? What are the effects of improving transparency of costs?	How can patient flows be designed in a way that maximizes efficiency and improves patient outcomes? How can novel inventory replenishment models ensure availability of supplies and minimize costs?	Dynamics of worker burnout (Homer, 1985) "Rookie-Pro" aging chains that account for heterogeneous productivity of experienced vs inexperienced employees (BD-19.1 and 19.2)
Human Body and Disease Prevention	Abdel-Hammid (2003), Jones et al. (2006), Karanfil and Barlas (2008), Abdel-Hammid et al. (2014), Fallah-Fini et al. (2014), Ghaffarzadegan et al. (2016), Hosseinichimeh et al. (2018), Rogers et al. (2018)	Stock and flow structures inside the human body (BD-6)	What are the government policies or behavioral interventions that can most cost effectively help contain the spread viral diseases?	How to manage healthcare operations during humanitarian operations in areas with poor infrastructure? How to manage the complications in regions affected by war, corruption, or related issues?	Treatment starves prevention structures (Jones et al., 2006)
Addictions and Pharmaceutical Use	Paich et al. (2011), Wakeland et al. (2011), Wakeland et al. (2015), Azghandi et al. (2018), Kunc and Kazakov (2018)	Aging chains (BD-12)	What are the government policies or behavioral interventions that can most cost effectively help drug epidemics?	How can critical drug distribution be improved in emergencies?	Treatment starves prevention structures (Jones et al., 2006)

*Source of question is from authors as opposed to from research agendas in sample papers

**Unless otherwise indicated, SD structures can be found in Sterman (2000), which summarizes seminal research in system dynamics, and presents many of the commonly used structures and formulations for a wide variety of modeling applications. For ease of reference, we will note the Chapter and Section where a relevant structure is presented as "BD-xxx yyy" where xxx is the chapter and yyy is the section.

1.4.3 Conflict, Defense and Security

Conflict, whether in prosecuting "conventional" warfare, suppressing terrorism, or acquiring military assets, is by definition an expression of policy goals. Most often, governments implement these policies with OM levers. This is perhaps unsurprising given that much supply chain and operations management is derived ultimately from operations research, which finds its origins in military planning. In particular, conflicts often center on classic operations management topics such as supply chains (e.g., logistics, inventory, infrastructure), force (i.e., personnel) planning, project management, procurement, and, recently, the information management/operations interface (Van Creveld, 2004, 2010). That said, a number of problems involve significant complexity due to sociological issues such as regime legitimacy. In addition, these problems often exhibit an extra layer of complexity due to the involvement of actively hostile actors whose objectives are completely at odds with those of other stakeholders. In this policy domain, there is a long history of intellectual thought that is particularly compatible with SD research. For example, scenario planning is derived in many respects from military wargaming, so much so that even private-sector firms often use the two terms interchangeably, particularly in OM. Similarly, since the 1800s, military decision-making has explicitly incorporated feedback thinking in the "command-and-control loop" (Van Creveld, 1985, Lofdahl, 2006). Boyd's observe–orient–define-act (OODA) loop is one well-known instantiation (Boyd, 1995, Plehn, 2000, Richards, 2020). However, many applications of SD that address problems in this cluster are never published, making the researcher's task more difficult (Coyle et al., 1999). However, Ford and Clark (2019), in their recent survey of the literature show that this had been somewhat remedied in the areas of "conventional warfare" and weapons systems acquisition.

The oldest stream in conflict, defense, and security (CDS) research appearing in our sample includes that of conventional warfare, particularly force planning and deployment (e.g., Coyle (1981), Wolstenholme (1983)). Unsurprisingly, given the military context, research in this stream pioneered some of the earliest uses of scenario planning (e.g., Coyle (1981)), numerical optimization (Wolstenholme and Al-Alusi (1987)), and the use of flight simulators for training (Coyle et al., 1999). In a slightly different vein, SD researchers explicitly addressed the feedback between human decision-makers' ability to execute the command-and-control loop with respect to managing supply chains and force deployment using improved information and sensor technology (Bakken and Vamraak, 2003, Lofdahl, 2006). Lastly, Artelli et al. (2009, 2008) is an exemplar of extending operations research concepts to include psychological and political science constructs. Specifically, they extend the classic Lanchester Laws—which define the odds ratio of a larger force winning as a function of its numerical advantage in troops—to include endogenous factors such as troop fatigue and public morale.

Project management, procurement, and implementation is one of the largest areas of SD research, because SD is well suited to project rework and other feedback loops. Much of this work has treated defense project management and acquisition (Lyneis and Ford, 2007). In our sample, this is reflected in the large number of papers on project management, a core OM discipline. SD can also assist project management due to its ability to handle many factors often omitted by OM work using other methods. For example, Lyneis et al. (2001) developed a model of air defense system procurement to check the bid, identify and manage risks, and assess the benefit of several process changes. They span silos into organization management to include team design. Another exemplar, Ford and Dillard (2008), examines how different OM project management strategies used (i.e., agile vs. waterfall) compare in operational effectiveness. For example, while using agile project management may expedite equipping some troops with improved weapons systems, this comes at the expense of delays in equipping other units.

Insurgency research should integrate decisions around the planning and effectiveness of prosecuting insurgent or counterinsurgent actions with organizational recruiting, demographics, propaganda, public pressure, political legitimacy, building, and finance. Due to the large number of mutually interacting factors and other system complexities, as well as feedback loops among these factors (e.g., collateral damage from missions to suppress insurgencies increasing insurgent numbers), researchers have found SD to be a particularly useful methodology (Choucri et al., 2007, Pruyt and Kwakkel, 2014, Richardson, 2005, Anderson, 2007b). One example of this work, Anderson (2011), spans all the silos just mentioned except for finance. On the methodology side, the paper uses dynamic optimization to study force allocation and the timing of force withdrawal. The paper also includes operational issues specific to the military, such as experience curves being driven by the cumulative number of actions taken by an opponent.

Generally, SD studies of operations in conflict, defense, and security are rather sparse, so all areas of inquiry could prove fruitful. However, studies on the criticality of information systems to the command-and-control loop would seem to be particularly amenable to the strengths of SD (Lofdahl, 2006). Studying the relationship between insurgencies, finance, publicity, and organized crime would be extremely useful given the damage of organized crime to society, such as drug trafficking and kidnapping for ransoms (Schoenwald et al., 2009, Schoenenberger et al., 2014, Saeed et al., 2013). These papers point to some paths that should be taken in this space.

Finally, there is spillover between CDS issues and other clusters, such as humanitarian operations. For example, the decades-long conflict in the Congo has led to a widespread famine that affects over 20% of the population and has created the need for extensive humanitarian aid (Programme, 2020). Famines also often lead to epidemics. Studying policy interventions that interact with humanitarian and healthcare operations would be an excellent use of SD's strengths. Table 1.5 below summarizes and organizes the research roadmap for this cluster, as described at the beginning of the section.

Table 1.4: Conflict, Defense, and Security Literature and Open Questions					
Research Topics	**Selected References**	**Useful SD Features**	**Policy Questions***	**Operational Questions***	**Relevant SD Key Structures for Future Research****
Literature Review	Cunico et. al (Forthcoming)	Causal representation in SD models provides insights Due to the lack of physical attacks to draw data from, simulation and scenario analysis are key.	How can threats be mitigated in an increasingly interconnected, and more technologically dependent world? How do we train personnel to cope with conflicts (e.g., wargaming)	What are the effects of militarily hostile "stakeholders" objective functions on operations?	Flight simulators (Coyle et al., 1999; Sterman et al., 2013) Adversarial decision making (Martinez-Moyano et al., 2015) Artelli et al. (2009, 2008) Scenario analysis for conflicts (Anderson, 2011), Coyle (1981)
Conventional Warfare	Coyle (1981, 1989, 1992, 1996), Wolstenholme (1983, 1988), Wolstenholme and Al-Alusi (1987) , Artelli and Deckro (2008), Artelli et al. (2009), Backus et al. (2010)	Relaxes the assumptions of the traditional force-loss ratio models (Lanchester Equation), to allow for conflicts that don't end in total annihilation or predetermined force numbers	How do we create and maintain effective military forces? How can the command-and-control loop be improved?	How to manage the complications in regions affected by war, corruption, or related issues? How can technology improve the speed of the command-and-control loop? How can processes be developed to prevent control loop disruption, particularly of information systems?	Ageing chains for recruitment including vacancy creation and hiring delays. BD (19.1) Maintenance structures for infrastructure, vehicles, etc. (BD 2.4) Decision support systems for military operations (Lofdahl, 2006, 2014)
Defense Acquisition and Capacity Planning	Lyneis et al. (2001), Bakken and Gilljam (2003), Bakken and Vamraak (2003), Lyneis and Ford (2007), Ford and Dillard (2008), Ford (2009), Ford and Clark (2019)	Highlights the tradeoffs and benefits of preventive policies versus reactive responses. Allows for exploration of different policies	How can defense acquisition costs be reduced while improving effectiveness?	Can agile or other project management methodologies improve acquisitions? How can organizational structures be designed to facilitate acquisition?	Project management models with rework, modularity, etc. (Lyneis and Ford, 2007) Organizational structures for acquisition (Ford and Clark, 2019)

Table 1.4: Conflict, Defense, and Security Literature and Open Questions					
Research Topics	**Selected References**	**Useful SD Features**	**Policy Questions***	**Operational Questions***	**Relevant SD Key Structures for Future Research****
Insurgency and Counterinsurgency	Coyle (1985), Richardson et al. (2005), Anderson (2007b), Choucri et al. (2007), Sardell et al. (2009), Schoenwald et al. (2009), Anderson (2011), Saeed et al. (2013), Pruyt and Kwakkel (2014), Martinez-Moyano et al. (2015)	Explores the effects of timing on the effectiveness of engagement and withdrawal efforts	How can the interconnectedness of insurgencies with other policy challenges be managed? What policies can manage the "business" aspects of insurgencies including links with organized crime?	How are increasingly global and interconnected SCs making governments more vulnerable to threats? How can supply chains for weapons etc. to support insurgencies be disrupted? How can funding for insurgencies and terrorism be cut without increasing organized crime?	Insurgency-crime dynamics (Saeed et al., 2013) Blockading weapons imports and cutting finance to insurgents (Anderson, 2007a)
Infrastructure and Information Security	Martinez-Moyano et al. (2011), Schoenberger et al. (2014), Nazareth and Choi (2015), North et al. (2015), Armenia et al. (2019)	Bass diffusion and SEIR epidemiological models to cyber virus attacks.	How can we protect critical infrastructure from terrorism in a cost-effective manner?	Is it better to use redundancy or some other method to increase resiliency? Are there new technologies to help predict attacks? How can we change managerial behavior to adopt a "security mindset?"	Using AI to predict attacks on infrastructure (North et al., 2015) Behavioral models of information security (Martinez-Moyano et al., 2011, Armenia et al., 2019)

*Source of question is from authors as opposed to from research agendas in sample papers

**Unless otherwise indicated, SD structures can be found in Sterman (2000), which summarizes seminal research in system dynamics, and presents many of the commonly used structures and formulations for a wide variety of modeling applications. For ease of reference, we will note the Chapter and Section where a relevant structure is presented as "BD-xxx yyy" where xxx is the chapter and yyy is the section.

1.4.4 Transportation, Logistics, and Infrastructure

One core area of study in operations management is transportation, logistics, and other infrastructure. This may not seem to involve complex systems, and hence, it may not seem a good fit for SD approaches. However, there is important research in our sample, and it suggests that including a certain level of complexity can be helpful under some circumstances. Prominent complexity issues often involve long delays between policy decisions, customer response, and outcomes.

The model of bus maintenance by Bivona and Montemaggiore (2010) is an exemplar of how SD can create counterintuitive policies by considering human factors and "marketing" issues endogenously. Including these factors results in a twist on the expected policy of reducing availability in the short term; instead, it favors preventive maintenance to reduce long-term cost. Surprisingly, the best strategy not only increases preventive maintenance, but also reduces the age of the bus fleet and frees up experienced mechanics to teach newly hired and inexperienced (or "rookie") mechanics. While these actions in fact raise long-term costs, they also lead to increased service quality and customer usage, resulting in higher profitability. This paper is also an exemplar of actively describing the use of group model building with, among other things, flight simulators used by city officials to determine policy priorities. Mayo et al. (2001) is another exemplar that examines many of the same issues with respect to the London Underground, using officials to build a flight simulator and develop scenarios. While the flight simulator is discussed at length, the authors used the flight simulator as a decision-support tool. It helped officials outsource their operations by evaluating bidding firms for their ability to run the underground system.

System dynamics addresses the role of OMPP in innovation in transport (Keith et al., 2020). Naumov et al. (2020) is an exemplar in this space, because it expands the boundaries typically considered in mass-transit planning to include not only new technologies, but also (1) expansive economic models of consumer utility and resulting market share, and (2) operational issues of maintenance and service routes run. For example, in their model consumer utility includes the belief by many policy experts that automated vehicles are problematic for improving the environment; these vehicles increase the attractiveness of commuting by reducing transit times and allowing drivers to spend their "drive-time" directly on work-related activities. Hence, experts argue for policies to increase ride-sharing), which, however, reduces mass-transit ridership. The model strongly suggests that policies promoting ride-sharing will reduce mass-transit capacity by strangling the funds needed for reinvestment. This could increase, rather than decrease, both pollution and energy use. Instead, a better policy seems to be a tax levied on vehicle miles traveled; this tax is then directed in part to the mass-transit system's upkeep. This paper also conducts an extensive, explicit analysis of trajectories that reveal path dependence and other issues via phase-plot analysis.

Another aspect of operations management addressed in an SD OMPP model is Pierson and Sterman (2013), an exemplar that examines how yield management strategies in the United States interacted with deregulation to create cyclicality in the airline industry's capacity, airplane production, and consumer demand. They find that yield management dampened capacity cycles but increased profit volatility, leading the airlines to lower average profits and reduced viability.

A last aspect is skilled worker infrastructure. Ghaffarzadegan et al. (2017) is an exemplar for future research in this area. It examines the mismatch between work needs in the economy and education as a function of policy. It does so by creating, in their words, an "operational model" that combines a queuing model as influenced by a number of government policies, university capacity decisions, and individual behaviors. The paper then explores the model's behavior under disruptions from the macroeconomy and other factors, using sensitivity analysis and scenario testing. One intriguing finding is that disruptions often result in shortages in filling lower-skilled jobs. This is particularly interesting given current shortages of workers in the U.S. and Europe in lower-skilled supply chain jobs such as warehouse workers, port employees, and truck drivers (Camaniti, 2021). The authors also discuss how their model could be extended to examine whether job-training policies create shortages of skilled workers needed for new technologies.

Several questions regarding transport and logistics policy remain open, many of them involving interactions with other policy areas such as sustainability and new business models. For example, the COVID-19 pandemic has accelerated the move toward online business models, which in turn has intensified the last-mile problem and led to the creation of more emissions. In addition, retail outlets may be weakened in urban areas due to the pandemic-driven "flight" to the suburbs, further intensifying the last-mile problem (Bloch, 2021). This may lead to a need for policies that accelerate the shift to alternative fuel vehicles and increase reliance on new business models, such as using "ride-share" companies that pool deliveries to reduce the average mileage driven per package delivered. However, these policies must also avoid weakening mass transit. How will new business modalities, such as working online, affect these decisions (Naumov et al., 2020)? Another open issue is the need to create policies to manage automated driving and flight (Naumov et al., 2020). Automated driving must be regulated for safety purposes, and new infrastructure may be needed. Automation might also lead to counterintuitive effects such as job losses from unemployed drivers. With respect to flight, regulation will be needed to cope with new modalities of delivery such as drones. How can drone parcel deliveries be done safely on a large scale, by many different business and organizations (Zelinger and Sallinger, 2020)? One possibility is to require pilot licenses when commercial drones operate beyond visual range, but that may damage the cost-effectiveness of drones, particularly if these devices can lower fossil-fuel emissions. This ties in with educational policies that create national workforces inappropriate to new economic and operational needs. How can policies be designed to avoid worker shortages in supply chain and emerging high-tech jobs in operations (Bowman, 2021, Van den Bossche et al., 2020)?

Table 1.6 below organizes the roadmap for the cluster as described at the beginning of this section, and it also provides additional references from our sample.

Table 1.5: Transportation, Logistics, and Infrastructure Literature and Open Questions

Research Topics	**Selected References**	**Useful SD Features**	**Policy Questions***	**Operational Questions***	**Relevant SD Key Structures for Future Research****
Literature Review	Abbas and Bell (1994), Shepherd (2014)	Clarify the relations between multiple stakeholders with different goals	What policies encourage transport and logistics efficiency and sustainability gains?	What sorts of new business models should be encouraged to improve operational efficiency?	Group model building to elicit decision maker's mental models.
Mass Transit	Coyle and Gardiner (1991), Homer et al. (1999), Mayo (2001), Bivona and Montemaggiore (2010)	Shows the effects of "induced demand" and why road building is a "policy resistant" alternative to reducing traffic	What policies can be enacted that can ensure the attractiveness, and improve the economics of mass transit?	How do we coordinate price setting and long-term maintenance and purchasing?	The mass transit "death spiral" (Naumov et al., 2020)
Highway Maintenance	Chasey et al. (2002), Friedman (2006), Fallah-Fini et al. (2010)	Combination of SD and optimization to improve priority setting schemes	How do we improve infrastructure functionality while reducing long term infrastructure costs?	What maintenance schedules should be followed? When should we build new infrastructure?	Maintenance structures (BD-2.4)
Airlines, Airport and Other Infrastructure	Liehr et al. (2001), Rudolph and Repenning (2002), Miller (2007), Pierson and Sterman (2013)	Models of supply line acquisitions that incorporate operational decisions such as revenue management	What is the impact of COVID-19 on transportation and logistics policies?	To what extent will telecommuting reduce traffic congestion and flying?	Aging chains that allow for heterogenous attributes of different stock vintages. (BD-12.1)
Innovation in the Automobile Market and Alternative Fuel Vehicles	Struben and Sterman (2008), Stepp et al. (2009), Kieckhäfer et al. (2014), Keith et al. (2019), Bhargava (2020), Keith et al. (Forthcoming), Naumov et al. (2020)	"Chicken-egg" dynamics in two sided markets	How should automation be regulated?	What are the unanticipated effects of policies to encourage automation that may lead to increased congestions? How can alternative fuel vehicles be incentivized or made attractive for last-mile deliveries?	Platform competitions under technology changes (Anderson, 1996). Also summarized in BD-10.4 Congestion modeling (Naumov et al., 2020)
Skilled Worker Infrastructure	Ghaffarzadegan et al. (2017)	Feedback between current workforce structure and managerial decision making	How to create a workforce that can maximize competitiveness?	How do we incent universities to encourage students to study the skills most useful to long-term national needs? How do we incent firms to offer ongoing training?	"Rookie-Pro" ageing chains that account for heterogeneous productivity of experienced vs inexperienced employees (BD-19.1, 19.2) Homer assignment model for resources (1999)

1.4.5 Sustainable Operations

Sustainable development was defined famously by the World Commission on Environment and Development (WCED Strategic Imperatives' 1987) as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs." At the heart of this issue are questions about how society consumes resources—both renewable and nonrenewable—in the presence of lengthy time delays between actions and consequences. This is complicated by the potential for self-interested and short-term behaviors that are at odds with the difficult collective actions needed to achieve true sustainability. As in other areas of policy, here governments can enact sustainability policy that align the incentives of individuals and firms with the collective good in principle. However, once again, system complexity often leads to unintended consequences and counterproductive policy-making (Moxnes, 1998, Moxnes, 2000). Another driver of complexity, at least in some contexts, is the need to model ecological or climate factors (Moxnes, 2005, Fiddaman, 2007). For these issues, SD modeling can be particularly useful in developing effective sustainability policies.

Moxnes (2005) is an exemplar of an SD model that includes domain data (from ecology), economics, and operations. The larger task is to determine the impact of optimal quotas and capacity decisions on the fishing fleet for preserving the Northeast Arctic cod fishery. Moxnes found, contrary to conventional wisdom, that optimal policies and their trajectories were affected more by uncertainties in nonlinear economic relationships than those regarding the ecosystem. His method may likely apply to many other sustainability settings; that includes climate change, the management of which has proven particularly problematic. Also, this is one of the few SD papers that uses stochastic optimization, which has the added benefit of enabling an examination of the optimal trajectories as a function of uncertainties.

Another exemplar is the study by Kapmeier and Goncalves (2018) that developed a model for managing tourism to promote economic growth, using 38 years of data from the Maldives Islands. Their model also included extensive input from various expert stakeholders from the island chain with respect to their concerns, decision-making policies, and other issues. Operationally, the study included capacity and demand as well as waste management, and it performed scenario planning to develop robust policies using Monte Carlo analysis. The authors found that policies for improving waste management will not work alone; one must also limit tourist demand.

Agrawal et al. (2019) used systems thinking techniques based on those discussed by Senge (1990) to identify new opportunities for research in sustainable operations, specifically circular or "closed-loop" supply chains. These transform the linear "take-make-dispose" industrial model into a circular economy that regenerates and restores materials, products, and other resources for future use. These strategies consider three important building blocks that are particularly germane to SD: “reverse flows,” “circular design,” and “circular business models.” All three explicitly consider feedback in their decision, production, delivery, and product transformation processes. Closed-loop supply chains have been studied with some success. Modeling examples include Lehr et al. (2013), which evaluates a variety of strategies for electronics firms to meet increasing European Union regulation of waste most effectively, and Yuan (2014), which studies the design of construction-waste fees charged in China.

Interesting questions remain open. For example, despite the significant number of insightful works addressing how firms must cope with sustainability policies, studies examining how to optimize macro policies in our sample generally offer model operations as simplified national or global aggregations (Fiddaman, 2007, Fiddaman, 2002, Rooney-Varga et al., 2020). They do not examine the implications at a micro level for manufacturing and supply-chain design that may affect firm viability and other allied issues, which Joglekar et al. (2016) argue is necessary. This is unfortunate, because studies in climate change, resource and land use, and circular economies are a rapidly growing field of operations management and, arguably, the most important. Furthermore, the number of feedbacks and delays is perhaps even greater in sustainability than in any of the other policy areas discussed in this paper. We urge more development in all the areas identified above. Moxnes (2005) and exemplars from the related fields of transportation and logistics or energy clusters could be used as models to emulate (Ford, 2008).

One area of inquiry not yet researched to the best of our knowledge is how to increase the durability of products, which could reduce both the future usage of materials and the creation of waste (Goworek et al., 2020). Another question is how continuous improvement programs might be actively directed to improve sustainability alongside regulatory changes. “Lean” continuous process improvement could be a powerful tool here, because its prime tenet is to “minimize waste.” However, continuous improvement takes time. Would abrupt regulatory changes (e.g., the sudden introduction of a carbon price) encourage the incremental minimization of waste, or would they result in risky “big bang” process-improvement projects? Similarly, firms might use process improvement to reduce their carbon footprints (Aguado et al., 2013), but what sorts of regulation, carbon taxes, cap and trade, etc., would be needed to drive firms to effectively minimize their carbon footprints using continuous improvement?

Table 1.7 in the below organizes the roadmap for the cluster as described at the beginning of this section and provides additional references from our sample.

Table 1.6: Sustainable Operations Literature and Open Questions

Research Topics	Selected References	Useful SD Features	Policy Questions*	Operational Questions*	Relevant SD Key Structure for Future Research**
Literature Review	Abdelkafi and Täuscher (2016), Rebs et al. (2019)	Clarify the fundamental tension between the desire for unlimited growth with limited resources	How can we rethink the concept of "sustainable growth"?	What are the appropriate time horizons for evaluating sustainable operations models?	Compared to analytical models and mathematical programming, simulation models are underrepresented in sustainability SD models of expectation formation, uncertainty and risk (BD-16)
Models for Climate Change and the Environment	Fiddaman (2002, 2007), Kunsch and Springael (2008), Sterman et al. (2012), Currie et al. (2018)	Interactive flight simulators for understanding and communication Understanding overshooting systems	What is the right communications strategy to educate decision makers on climate policy? What is the impact of technological change for sustainability operations?	How should we design flight simulators to improve stakeholders' intuition?	Flight simulator design (Sterman et al., 2013) Feedback loop between technology and sustainability (Fiddaman, 2007)
Planning, Development and Construction	Saysel et al. (2002), Shen et al. (2005), Kapmeier and Gonçalves (2018)	Model the tradeoff between growth and environmental impacts	What is the rate at which regulation target levels be raised? Should they be continuously increasing or "lumpy?"	How do regulations impact capacity planning?	Models that include social aspects of Sustainable Development (Kapmeier and Gonçalves, 2018)
Resource Management, Circular Economy and Closed Loop Supply Chains	Moxnes (1998, 2004, 2005), Mendoza and Prabhu (2006), Georgiadis and Besiou (2008, 2010), Purnomo and Mendoza (2011), Bhattacharjee and Cruz (2015), Do Val (2019)	Broad model boundaries allow for analysis that incorporate both the environmental and economic aspects of sustainability	What is the role of legislation in achieving compliance?	How do different regulation or incentive structures affect individual industries, and how do they affect operations at firm level? What is the impact of production techniques on sustainability?	Models that include social aspects of Sustainable Development (Kapmeier and Gonçalves, 2018) Scrap reduction from Lean Manufacturing. (Gupta et al., 2018)
Fuel Economy, Emissions and Waste Reductions	BenDor (2012), Lehr et al. (2013), Saysel and Hekimoglu (2013), Yuan (2014)	Induced demand Rebound effects	What is the optimal recycling percentage that should be pursued?	How should lifetime recycling policies be designed to best encourage compliance? What incentives would drive production of durable products?	Aging chain structures for age of product vs. likelihood of disposal (BD-12)

1.4.6 New Business Models

Since 2000, there has been a flurry in the development of new business models. While many have been driven by improved information technology such as the internet, they also rely on operational innovations such as online ordering and home delivery. This has attracted the interest of OM researchers (Kumar et al., 2018, Sorescu, 2017). This area, ripe for policy and regulation, is clearly a complex system. The seminal work Parker et al. (2016) explicitly uses the language of SD, defining platforms as the center of reinforcing loops that connect different markets. While these markets are not owned by the platform firm, they create value for each other. Uber is a classic example of a firm that exploits the cross-side externalities between passengers and drivers, in which more passengers attract more drivers, which attract more passengers. To enable this often requires an operational innovation. Uber replaced employees with freelance "gig workers" who essentially act as spot-market suppliers. However, the book also discusses the negative effects of platforms on the community. For example, Uber's drivers do not receive health insurance, monopoly effects might harm service and affect antitrust policy. Despite this rich discussion using SD terminology and concepts, however, there is no associated simulation model. Very few other extant SD research articles use models that analyze policy for platforms. This is unfortunate, because most of the extant literature on platforms, on which much policy is being decided, employ single-period game theory models. That said, there are a few SD papers treating OMPP issues in platforms. These include the study by (Keith and Rahmandad, 2019) of winner-takes-all outcomes in the gig economy. Another is the study by Anderson and Parker (2013) of an energy power storage startup's new product-development choices in technology; it explicitly considers cross-side externalities as well as funding mechanisms for startups. However, both papers could easily have done more to study potential public-policy interventions.

Startups are their own business models, differing from mature firms in important ways, such as their lack of cash combined with the need to balance R&D, marketing, capacity, and production during rapid growth. These lead to OM problems that lend themselves to SD research (Bianchi and Bivona, 2002, Milling and Stumpfe, 2000, Paich and Sterman, 1993). Another issue is that the overwhelming majority of startups fail (Marmer et al., 2011). SD models are particularly useful here because it can study unsuccessful firms and avoid the survivor bias when studying only those firms that "make it." Policymakers often see startups as desirable, and the U.S. and other countries have policies to encourage startups (Hsieh and Chou, 2018). However, that raises two questions. Which policies actually help startups while also avoiding unintended consequences? And which policies, such as tax laws, inadvertently hurt startups and small enterprises? While SD studies are strongly indicated, published studies are currently rare (Zali et al., 2014).

Questions around new business-model policy are plentiful. For example, should gig employees be treated as independent contractors? But these issues remain understudied by SD scholars. There are many other issues that, to the best of our knowledge, remain completely unstudied. For example, the shift to more online ordering has led to interest by OM scholars in the last-mile problem created by increased deliveries as well as increased problems in reverse-logistics. This has a variety of knock-on effects that may need regulation. For example, increased vehicle emissions may potentially increase government interest in accelerating requirements for alternative fuel vehicles, which has been discussed previously. Waste-management problems also increase as a function of extra shipping materials and returned goods (Slabinac, 2015). Further, while warehouse workers represent a larger section of the economy, they are perceived to be underpaid or otherwise exploited by firms such as Amazon. As it has with gig workers, this situation has led to calls for employment regulation (Long, 2018), which may have unintended effects such as the acceleration of automation. SD models could be helpful in studying all these issues.

With respect to new business models that rely on externalities, several questions need to be studied, especially those relating to operations and policy, such as antitrust issues. For example, Amazon's reverse engineering of popular products from small and medium enterprises is now being investigated as a potentially unfair trade practice (Kalra and Stecklow, 2021). However, are regulatory remedies truly necessary, given that other platforms such as Shopify and BigCommerce are creating systems to enable small and medium enterprises to compete with Amazon (Lu, 2020)? Also, to the best of our knowledge, SD studies of the interaction of open or crowdsourced innovation with policy is completely absent. How should startups be promoted more broadly through policy? For example, could some worker regulations that make sense for large enterprises be problematic for small enterprises? Ultimately, policies are needed to encourage this development in nations that have a chronic shortage of the skilled labor needed to maintain automation, such as the United States (Moreno and Bauer, 2017). Similarly, to the best of our knowledge, additive manufacturing—better known as rapid prototyping or 3D printing—has also not been studied. This area is ripe for regulation given the possibilities for intellectual property (IP) infringement and the production of dangerous or other undesirable products, such as handguns. At the same time, additive manufacturing is desirable for encouraging R&D and leveraging open innovation. It also could have been used during the COVID-19 pandemic to produce critical subcomponents for equipment with otherwise disrupted supply chains. Another area of new business models includes those based on disruptive technologies in operations such as artificial intelligence, machine learning, and automation. Much of this is covered in the transportation, logistics, and supply chain section of this paper, and includes Naumov et al. (2020). Much is also captured by prior SD models, such as Forrester's, if parameters are used to reflect improved forecasting accuracy and promote coordination. However, some applications of artificial intelligence (AI) need new models. For example, the rise of automation requires a new type of labor force, one with fewer unskilled workers and more who are skilled. However, the U.S. is chronically short of skilled workers, so how can this be remedied?

In short, the literature in all these topics is sparse, the suitability of SD is high, and the importance of policy questions is of the utmost importance. Table 1.8 below organizes the roadmap for the cluster as described at the beginning of this section and provides additional references from our sample.

Table 1.7: New Business Models Literature and Open Questions

Research Topics	Selected References	Useful SD Features	Policy Questions*	Operational Questions*	Relevant SD Key Structures for Future Research**
Entrepreneurship and Start-ups	Paich and Sterman (1993), Bianchi and Bivona (2002), Oliva et al. (2003), Sterman et al. (2007), Zali et al. (2014)	Boom and Bust Dynamics Limits to Growth	What are policies needed to encourage new business model innovation to best enhance operational efficiency and social welfare?	What supply chain (SC) models result from new business models? How can regulators design antitrust regulation to enhance operational effectiveness in a SC ecosystem? What policies will encourage a firm's new product development?	Startups and integration of complementary products (Anderson, 1996) "Market Growth Model" for scaling new businesses. (BD-15) "Design win" model for new product development pipeline
Automation	Nieuwenhuijsen et al. (2018), Naumov et al. (2020), Yu and Chen (2021)	Models of innovation diffusion Broader modeling boundaries for analysis of so-called "unintended consequences" of interventions	What policies should be in place to promote startups and small and medium enterprises' innovations?	How can the innovativeness of small and medium firms be measured? How will regulation and taxation policies affect startup and SME operations differentially from large, mature firms? How can large platforms be prevented from suppressing IP infringement?	Innovation diffusion models coupled with product "hype cycle" dynamics. (BD-9.3)
Platforms	Anderson and Parker (2013), Parker et al. (2016), Keith and Rahmandad (2019)	Models that combine SD and game theory	How should new business models such as platforms be regulated?	What are the operational effects of converting "gig workers" to employees? How can waste production by online firms' deliveries be reduced?	Platform models of demand, technology, and supply (Anderson, 1996) Search on complex landscapes (Rahmandad, 2019)
R&D and Product and Process Inter-dependencies	Anderson (1996), Milling and Stumpfe (2000), Akkermans and van Oorschot (2016), Hsieh and Chou (2018)	Models for project management, and concurrency for "strange projects" that face many unknown risks (Pitch et al. 2002, as quoted in Akkermans and van Oorschot 2016)	What policies are needed to manage new technologies and their potentially deleterious effects?	What is the effect of automation on reduction of a firm's unskilled workforce and increase in skilled employees? How should 3D printing be regulated to increase safety and reduce IP theft without stifling innovation and improving supply chain resilience?	"Design wins" model of new product development pipeline Project models including concurrency, rework, etc. (Lyneis and Ford, 2007)

1.4.7 Energy

Parker et al. (2019) provides a scoping review of articles published on current operational and policy issues related to the electric power industry. The authors highlight the need for new models, to both help the industry better utilize resources in complex systems involving environments of increasing uncertainty and aid government policy makers better understand the potential impact of regulatory decisions. Specifically, they argue that there are opportunities for research recognizing the mutually interacting and dual-causality dynamics between operations and public policy. For these reasons, there is a long history of using SD models as a decision support method in the energy sector (Ford, 1997, Ahmad et al., 2016, Leopold, 2016). Work has spanned areas including fossil fuels, renewables (Fontes and Freires, 2018, Zapata et al., 2019), power generation and distribution (Ford, 2008), and the evaluation of alternatives for both utilities and governments (Johnson et al., 2006, Tan et al., 2010). Particular complexities handled in these models include uncertainty in technology development. Another issue is—at least in the U.S.—considerable fragmentation of the power-generation industry.

The literature in this space is burgeoning. Several review papers are helpful in classifying recent work. Teufel et al. (2013) proposed a categorization into regulated and liberalized electricity markets, and the authors further subdivide these two markets into a number of sub-categories. Leopold (2016) provides a detailed review of other works using SD to model energy related systems. Qudrat-Ullah (2015) conducts a review of different modelling and simulation studies in service energy policy, including system dynamics, linear programming, econometric methods, optimization, scenario analysis, and agent based models.

An exemplar article in this cluster is the study by Ford (2008) of technology choice, capacity planning, carbon-capture technology, incentives for switching to renewables, and pricing cap-and-trade allowances to reduce carbon emissions in the U.S. Western Energy Grid. Using extensive scenario testing in a model deeply grounded in technological detail, Ford found a number of results concerning different legislative and regulatory proposals, particularly that carbon pricing should be implemented even absent development of advanced technologies such as carbon capture and sequestration. A more recent exemplar paper by Castaneda et al. (2017a) builds a model including electricity demand and capacity markets to study the impact of roof-top solar systems on electric utilities' business models. It also includes the Bass marketing model for demand for rooftop solar capacity. They analyzed several scenarios based on input from stakeholders including managers, engineers, energy specialists, and policy makers to cope with the numerous uncertainties involved. The paper ultimately finds that some environmental policies promoting rooftop solar may actually increase the likelihood of a death spiral for utilities.

Other areas that have been studied by SD researchers include electricity market design, renewable integration, effects of climate policy on electric power infrastructure, the rise of electric powered vehicles, energy storage, and the growing interdependence between natural gas and electric power sectors (Arango and Larsen, 2011, Kilanc and Or, 2008). These often overlap with other areas of OM, such as sustainability, and further highlight the importance of the interdisciplinary study of complex topics. While there is a fair amount of SD literature with respect to OMPP problems in energy, the number of open questions remains extensive. Perhaps the most interesting are those that overlap with other clusters already identified in this paper. In particular, there is an obvious overlap between sustainability and energy. Hence, many of the questions related to combining energy models with climate models are critical (Fiddaman, 2002, Fiddaman, 2007). However, these questions must also include the impact at the micro-level operations issues faced by energy generation and distribution firms. A related question is: how can electricity systems be designed to cope with the extra capacity and uncertainty created by electric vehicles? For example, Bhargava et al. (2020) estimates that the load of a single electric truck is similar to that of a small city. There is also clear overlap between energy distribution, electricity markets, and new business models. For example, electricity grids are multisided markets and have cross-sided externalities with respect to technology adoption, particularly around power generation and storage (Parker et al., 2019) How does one account for these new business models when drafting regulations? Capacity decisions by utilities depend upon whether power markets are based on guaranteed capacity (as in the U.S. Eastern and Western Grids for electricity distribution) versus based purely on delivered kilowatt-hours (as in the Texas Grid). Which design is better, and under which conditions? Are there other designs that can combine the best parts of both? Or is some other design even better?

Table 1.9 below organizes the roadmap for the cluster as described at the beginning of this section and provides additional references from our sample.

Table 1.8: Energy Literature and Open Questions

Research Topics	Selected References	Useful SD Features	Policy Questions*	Operational Questions*	Relevant SD Key Structures for Future Research**
Literature Review	Ford (1997, 2020), Teufel et al. (2013), Qudrat-Ullah (2015), Ahmad et al. (2016), Leopold (2016), Parker et al. (2019), Selvakkumaran and Ahlgren (2020)	Models that allow for understanding of the dynamics of energy transitions Delays in the demand control loops and capacity acquisition generate cycles	How can we most effectively use regulation and to produce and supply energy in terms of cost, reliability, and sustainability?	How can we accurately forecast demand and match generation capacity in an increasingly decentralized market? How do we design markets to ensure reliable energy and utility viability?	Platform structures (Anderson, 1996) also summarized in (BD 10.4) Capacity acquisition behavior by managers Forecast structures and perceptions of other actors' forecast structures (BD 16)
Power Generation and Electricity Markets	Fan et al. (2007), Sánchez et al. (2008), Kilanc and Or (2008), Arango and Larsen (2011), Moumouni et al. (2014)	Models for project management (BD-2) Models that combine simulation with credit risk theory and game theory (Sánchez et al. 2008)	How can we develop a platform for electric power markets to better integrate distributed energy resources into power grids?(Parker et al. 2019) Do liberalized energy markets offer sufficient incentives for building generation capacity? How can the utility death spiral be avoided?	What's the impact of dynamic electricity pricing on capacity investments, demand response adoption, emission levels and technology mix of electricity generation portfolios? (Parker et al. 2019) How do different rate structures affect renewable energy capacity investments?	Prices and desired capacity (BD 20) Perception delays (BD 11.3) Yield management structures and capacity planning (Pierson and Sterman, 2013)
Clean Energy, Sustainable and Renewables	Movilla et al. (2013), Aslani et al. (2014), Franco et al. (2015), Osorio and Van Ackere (2016), Castaneda et al. (2017b), Fontes et al. (2018), Zapata et al. (2019), Liu et al. (2019)	Modeling competing scenarios	How does regulation & deregulation impact efficiency of integration of renewables into the grid? What market policies or regulations can help improve the large-scale integration of renewables?	How can renewables be used to secure supply, provide competitive prices, and provide environmental protection? What is the impact of large-scale renewable integration on optimal schedule and dispatch of power generation resources?	Design of energy storage technology in presence of grid platform effects (Anderson and Parker, 2013)
Evaluating Alternatives and Risk Management	Johnson et al. (2006), Tan et al. (2010), Jeon and Shin (2014), Shafiei et al. (2015), Fazeli and Davidsdottir (2017).	Modeling competing scenarios	Can clean energy policies be improved by bringing in an OM perspective?	How can operations and supply chain management be revised to reduce emissions?	See approximations for mileage in a vehicle routing problem (Figliozzi, 2009)

1.5. Discussion and Conclusion

In this work, we have sought to create a roadmap for researchers interested in using system dynamics to study operations management in public-policy-related contexts. Our intended audience includes both those experienced in using SD and those new to the field. To this end, we collected a sample of approximately 150 SD articles at the interface of operations management and public policy. The research areas surveyed are vast: including humanitarian operations; healthcare operations; conflict, defense, and security; transportation, logistics, and infrastructure; sustainable operations; new business models; and energy. Necessarily, we have imposed boundaries to keep the task manageable. For example, we avoided studies that represented operations at a macro level, typical of labor economics or macroeconomics research. While such research is valuable, it does not effectively inform operations management research. We also do not attempt to be exhaustive in our sample; instead, we focus on a scoping review, establishing a useful knowledge base for contemporary researchers interested in this area.

We leverage our sample in several ways. First, we describe why, when, and how SD models might be valuable for studying operations management problems in a public-policy context. Second, we identify the tradeoffs in data gathering, aggregation, optimality, boundaries, and other issues involved in using system dynamics models versus "classic" operations management modeling methodologies such as game theory, mathematical optimization, and queuing. Henceforth, we find this is often not an either-or question—nor should it be. Instead, multiple methodologies can and often should complement each other.

Next, we clustered the articles by topic. For each topic cluster, we then identified a list of extant literature, the extant contributions of system dynamics research, open questions, and potential SD building blocks for scholars investigating these questions. We gathered these into tables for each cluster to organize that knowledge for future researchers. We also identified and described exemplars in each cluster that could serve as models for future academic work.

Several overarching challenges, all common to multiple clusters, emerge for researchers in public policy-related operations. On the methodology side, the biggest area for potential improvement is researching the use of SD models for consensus-building among stakeholders. In our sample, we cite exemplars that document group-model building as well as the use of flight simulators (see Table 1.10 below, and note well: An "x" indicates an especially noteworthy use of a method. For example, all papers in the sample do rigorous sensitivity analysis. However, Ford's (2008) is particularly detailed and extensive, even relative to other exemplars, and is an excellent model for future researchers). However, overall, detailed literature remains sparse in the context of operations management for public policy. This is unfortunate, because stakeholder resistance is often a major hindrance to implementation (Besiou and Van Wassenhove, 2015). One simple step to improve research in this area would be providing more description on how stakeholder consensus is reached, even in papers primarily centered on the nature of the ultimate solutions. An exemplar for this approach is Goncalves et al. (2021), particularly because it describes a consensus-building approach different from those traditionally described in SD research (Andersen et al., 1997, Vennix, 1999).

Table 1.9: Summary of Noteworthy Use of Methods in Exemplar Papers

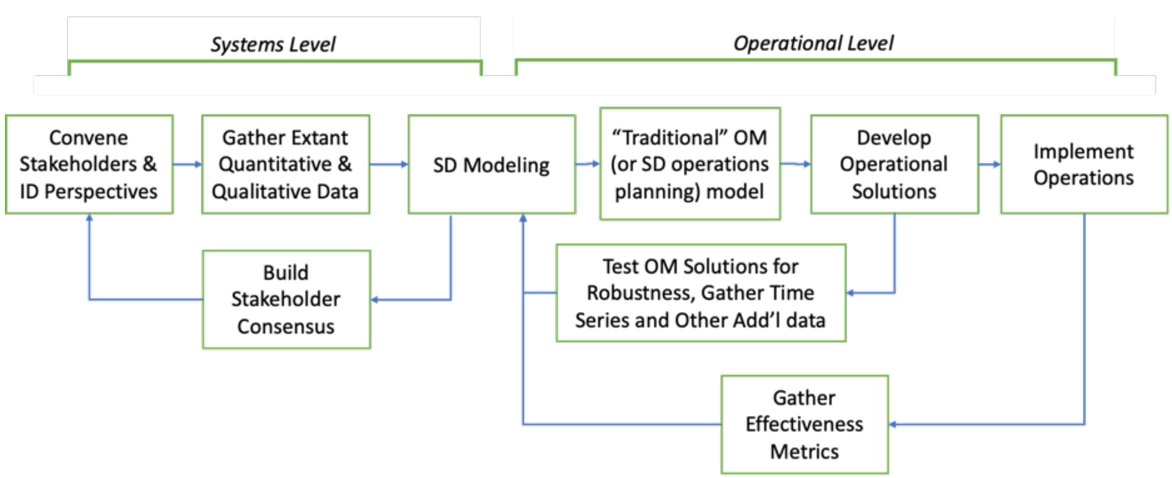
Exemplar	Topic	Sensitivity Analysis	Scenario Analysis	Calibration Against Time Series Data	Monte Carlo Sims	Trajectory Analysis	Dynamic Numerical Optimization	Integration with Traditional OM/OR	Group Model Building	Flight Simulators	Spans Discipline Silos	Notes
Anderson (2011)	Counterinsurgency for planning			X			X				X	Integrates sociology and political science concepts. Nontraditional experience curve based on enemy activity.
Artelli et al. (2008, 2009)	Psychological and political factors' effect on OR Lanchester Laws							X				Expansion of OR Lanchester Laws with psychological and political science constructs.
Besiou et al. (2014)	Central vs. local purchasing of relief vehicles				X			X			X	Tests against dynamic programming models. Addresses concept of "earmarking" by funding organizations.
Castaneda et al. (2017a)	Roof-top solar power incentives' effect on electric utilities								X	X	X	Uses Bass Diffusion Mode, from marketing literature.
Ford (2008)	Carbon reduction and technology choice by electric utilities	X	X									Extensive grounding in technical engineering literature.
Ford and Dillard (2009)	Agile development of weapons systems							X				Compares agile and waterfall project management methodologies.
Ghaffarzadegan et al. (2016)	Post-traumatic stress disorder management		X								X	Incorporates human psychological factors.
Ghaffarzadegan et al. (2017)	Workforce education	X	X					X				Incorporates a queuing model.
Gonçalves et al. (2022)	Healthcare capacity planning during pandemics			X					X			Uses nontraditional group model building techniques.
Kapmeier and Gonçalves (2018)	Sustainable island tourism		X	X	X							Connects a behavioral econ model of service industry to environmental impacts. Uses MC simulations to assess OMPP policies. Detailed consensus building.
Kang et al. (2018)	Public polices for chronic disease management		X									Integrates multi-object goal planning model, scenario planning, and a Markov model of disease progression.
Kunz et al. (2014)	Preparedness strategies for disaster relief	X	X									Extensive scenario and sensitivity analysis.
Kunc and Kazakov (2018)	Pharmaceutical competition for heart disease market									X		Transforms a developed model into a flight simulator for building consensus in a workshop for multiple stakeholders.
Lane et al. (2001b)	Reducing hospital emergency department waiting time			X					X	X		Uses time and motion studies to directly calibrate parameters rather than via optimization algorithms.
Mayo et al. (2001)	Subway vendor selection		X							X		Flight simulator used to teach vendors successful business models.
Moxnes (2005)	Quotas & capacity effects on fishery sustainability					X					X	Stochastic optimization. Integrated ecological modeling.
Naumov et al. (2020)	Autonomous vehicles, ride-sharing, and mass transit					X					X	Economic utility functions extensively used.
Pierson and Sterman (2013)	Deregulation and aircraft purchase cyclicality							X				Integrates yield management.
Thompson et al. (2015)	Polio eradication	X	X	X	X			X	X			Summarizes a series of articles. Incorporates game theory, linear programming, decision analysis, and inventory models.

Another challenge is the dearth of research on integrating SD with other OM modeling techniques, whether mathematical programming, queuing, or otherwise. Table 10 identifies some exemplars that have addressed this issue. Other than those exemplars, however, few papers have investigated this area. As a result, this represents an important area for future research. Ghaffarzadegan and Larson (2018) and Anderson (2019) have outlined several potential paths of inquiry. One possibility is to build on the SD model of Homer (1999) for managing service capacity, which solves an optimal assignment problem for each time period. Additional building blocks for this area include articles by various authors in the book edited by Rahmandad et al. (2015). Among other things, the chapters by various authors address the use of Markov chains, decision analysis, optimization, and game theory. A related issue that shows up repeatedly in our survey is the last-mile problem. Formulations from operations management exist that can approximate the mileage at an aggregate delivery level for a fleet of vehicles traveling within a geographic location (Figliozzi, 2009).

The topic of trajectories between the current and desired states is also a natural opportunity for system dynamics research (Moxnes and Davidsen, 2016). A particularly fruitful area to concentrate on is not only optimal trajectories between current and desired states, but also whether path-dependence precludes such a trajectory to that desired state. If that is the case, the question arises: What would be a useful path of inquiry, particularly when system dynamics models integrated with traditional operations management methods are employed? While this is implicitly discussed in some articles in our sample, explicit discussion is very sparse. One exemplar is Naumov et al. (2020).

Based on these findings, we propose building on the Besiou and Van Wassenhove (2015) framework for addressing OM problems in public policy, as shown in Figure 1.4 below.

Figure 1.4: SD Modeling Process for Operations in Public Policy Contexts



The major addition to their framework is a feedback loop on the left side of the model at the "systems level" to build consensus: convening stakeholders, gathering extant data at hand, and building small system dynamics models using a group modeling process. The goal is to facilitate stakeholder consensus on a systems-level approximation of what an operational solution might look like. We propose that in practice this feedback loop be pursued for several cycles before moving on to the detailed "operational level" on the right-hand side. Within the operational loop, more detailed operations planning models can be developed using traditional OM techniques such as mathematical programming or, alternately, by expanding the SD model appropriately to obtain an operational solution (or set of solutions). The potential solutions are then tested for robustness against the systems-level model, and additional data is gathered as needed. Every few cycles of the loop at the operational level, the proposed implementation should be fed back to the stakeholders at the systems level to gather input and maintain consensus. Flight simulators can be employed where appropriate. After a few more iterations between the two levels, the solution is implemented, and appropriate effectiveness metrics are gathered. These metrics should then be incorporated at the operational level to adjust the solutions to improve effectiveness and, from time to time, at the systems level to receive input and maintain consensus.

On the domain side, studying spillovers among public policy research clusters is a rich area for future research. The electric vehicle fast-charging stations problem, used as a motivating example earlier in the article, spans multiple areas: transportation and logistics, energy, and new business models. In another area—conflict, defense, and security—insurgency suppression involves questions that go beyond the purely military in nature, because insurgencies destroy infrastructure and food supplies, which in turn contribute to weakening a population with respect to disease. On the opposite side, military conflicts often hinder humanitarian operations in the area and endanger nearby personnel.

Finally, several opportunities for research emerge from recent global disruptions, including international trade disputes and the COVID-19 pandemic, that have laid bare the fragility of global supply chains. Research into bolstering these supply chains with policy initiatives (e.g., U.S. President Biden's "Infrastructure Investment and Jobs Act" initiative to increase infrastructure resiliency) is a fruitful and necessary area for exploration by researchers leveraging system dynamics. However, there is currently little, if any, SD research addressing these areas outside of supply chains directly related to medical devices and supplies. Some starting points do exist, and they could be built on. Coping with smaller-scale supply chain fragility occurs in articles in three clusters of our sample: humanitarian operations; healthcare operations management; and conflict, defense, and security. Some policy efforts emphasize near-sourcing. For example, the U.S. CHIPS Act of 2022 subsidizes firms building semiconductor capacity in the United States with the aim of reducing reliance on manufacturers located in Asia. Twenty years ago, some SD modeling research touched on the consequences of offshoring manufacturing, which included a hollowing out of nations' strategic manufacturing competencies (e.g., Anderson et al., 2000). In addition, Akkermans et al. (1999) developed an extensive set of causal loop diagrams around international outsourcing that included the impact of customs and regulations policies. Another potential building block comes from Joglekar and Phadnis (2020) and Phadnis and Joglekar (2021) which propose to expand scenario planning to cope with policy disruptions by including suppliers in the planning process, which is a natural fit for SD.

To conclude, we believe this survey describes how system dynamics can provide a powerful lens for studying policy issues in supply chain and operations management. Further, this work is intended as a roadmap for all researchers who might profit from using SD to address public policy problems, whether they have used SD before or are interested in trying it for the first time.

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Chapter 2

Leveraging Value Creation To Drive the Growth of B2B Platforms

Business platforms have become widespread in Business to Consumer (B2C) markets and their adoption is on the rise in the business to business (B2B) world. However, our understanding of platform adoption in B2B is less developed than for B2C. In the few cases where B2B platforms have been explicitly examined, it is often assumed that they can be understood using principles developed from the study of B2C platforms. However, the two types of platforms have important differences that often require different managerial policies to be successful. B2B supply chains are much more complex because of multiple echelons, the sophistication of their purchasing and other organizations, the competition they face, and the value of their data. The result is that, among other things, the nature of their value exchange is likely different. To address this gap, we create a novel framework. The value creation lens is grounded in theory and creates a better understanding of the dynamics of platform creation and growth by separating the platform's value into three components: (1) the standalone value of the product, such as a smartphone's ability to take pictures, (2) the value of other participants on the platform, such as the number of friends on Instagram or merchants on eBay, and (3) the value created by complementary products from 3rd-party providers, such as apps for a smartphone. A dynamic perspective explores the trajectory of differences in value between B2B and B2C platforms along with managerial implications.

Keywords: Platforms; Two-sided Markets; Business to Business; Business to Consumer; Value Creation; Launch; Scale

2.1 Introduction

Our goal in this paper is to explore an important emerging area, business to business (B2B) platforms, that we expect will be of substantial interest to production and operations management scholars. B2B platforms can be viewed as both standalone technological systems as well as business platforms that are designed to create and capture value from network effects. We have seen an explosion of investment in this area ranging from industrial internet of things technology (IIoT), agricultural technology, multi-model logistics tracking systems, medical system ecosystems, and much more.[1] Our work draws from and seeks to join elements of the information systems and operations management literatures that have for decades

[1] See for example, PTC, Siemens Mindsphere, John Deere's MyJohnDeere, Project44, GE Healthcare & Siemens Healthineers.

proceeded largely in parallel. In recent years, however, these fields are coming closer together, and it is gratifying to note that the *Production and Operations Management (POM)* journal now has multiple departments that explicitly cross the two fields. This should come as no surprise; *POM* has deliberately positioned itself to be an outlet to report on the study of operations management spanning a wide range of phenomena, methods, and applications over its now thirty-year history.

As an example of the convergence of POM and information systems research, platforms have emerged as a new type of supply chain relationship to deliver value. They have long existed in local forms such as medieval marketplaces and in narrow form, such as the spot markets that help to mitigate last minute supply and demand imbalances. However, advances in information and communications technology (ICT) and the digital transformation seen in many industries is broadening the application of platforms in supply chains. This can be clearly seen in business-to-consumer (B2C) relationships in which a consumer does not have to buy products from a department store that holds its own inventory. Instead, consumers can buy from a market platform such as eBay or Amazon Marketplace, both of which allow browsing among hundreds of "shop fronts." Consumers can also use platforms to bypass retail stores to buy directly from manufacturers, potentially on different continents. These alternate retail arrangements have been widely studied, particularly in the IS literature as the supply chains are straightforward.

Now, however, platforms are moving into the B2B arena as well. As case studies and media coverage continue to showcase the great successes of platforms in the B2C world, firms that serve other business customers in healthcare, manufacturing, and other industries are frequently asking whether the revolutionary successes of B2C platform-based supply chains might be replicated in their own markets. Might B2B platforms improve their profits through enhanced value delivery to customers? Should they sell to other supply chain echelons, or should they trade within their echelon? Should companies start their own platforms or join consortia to create joint platforms?

Platforms have been widely studied, through both a theoretical and empirical lens. However, we believe that academic theory treating B2B platforms lags industry and practice. Part of the reason is that extant data and theory on network platforms derive primarily from B2C settings, but B2B platforms differ in several ways from B2C platforms. Their supply chains are much more complex because of multiple echelons, the complexity of orders, and in many cases the type of value exchange (e.g., intermediate parts assemblies) being traded. For example, one echelon of a supply chain may have a traditional "pipe" one-to-one relationship, but the next echelon upstream may have a platform structure. As another example, establishing standards between echelons connected by a platform may be difficult because of the need for common digital *and physical* standards. Another difference is that many B2C platforms capture value in part through the acquisition and aggregation of customer data, which is then sold to third parties such as advertisers (Anthes, 2015). Business customers, however, are much more protective of their data for purposes of security and competitive advantage (Cusumano et al., 2019) although they may trade pre-competitive data within an echelon. Bargaining power between businesses and consumers in platforms primarily favors businesses but bargaining power between supplier and consumer in a B2B relationship can vary markedly. Because of these and other differences, current theory guiding the design, economics, and deployment may lead to different outcomes in B2B settings. That said, many, if not most, of these complexities involve supply chain and operations management. Hence, the POM community has much to say about these types of supply chain issues. As a result, we believe that POM scholars need to become partners with IS scholars to make fundamental progress in our understanding of B2B platforms as specialized supply chain arrangements.

To begin to answer the strategic and operational questions raised by employing platforms within supply chains, we begin by examining in more detail where B2B and B2C platforms overlap and where they differ. To this end, we develop and apply a framework based on how the platform impacts the exchange of value between supply chain members. We leverage prior research in information economics such as Parker and Van Alstyne (2018) and then apply supply chain and operations principles to create a novel framework, the "value creation lens." It separates the value created by a platform for its customers into three components: standalone value, same-side value, and cross-side value. The "standalone value" of the platform benefits the firm in some manner absent any externalities. It is generally POM-related but does not directly affect the nature of the supply chain linkage other than facilitating the extant linkage's execution. For example, one of the platforms in our data set uses an airline's maintenance data to create improved preventive maintenance schedules, hence improving availability and expediting delivery of replacement parts. The second is the "same-side value," that is the value of other participants on the same "side" of the platform. For example, the same platform just described could aggregate data among airlines. This would have the benefit of creating even better preventive maintenance schedules than it could utilizing only one firm's data. Moreover, this is a type of externality because the more airlines that participate, the better the recommended schedules will be. Importantly, the value exchanged is between firms in the same supply chain echelon, creating a lateral rather than upstream or downstream linkage. The third "cross-side" value is the value to participants of third-party providers on the other side of the market. For the airline maintenance platform, airlines would benefit from having more suppliers to buy replacement components from or analytics providers who could use airline data to deliver services to the airlines. This is another externality. All other things equal, the more suppliers, the more cross-side value to the airlines. The reverse is also true. The more airlines participating on the platform, the greater the cross-side value to the suppliers. Importantly, the value users receive from each of the three components is almost certain to change over time. For example, the relative value of each of the three bins in a startup may change greatly as it launches, grows, and then becomes a mature firm.

The use of this framework on a dataset describing 79 B2B platforms generates novel, interesting, and important insights into the differences that separate B2B from B2C platforms.

Among these insights are, relative to B2C platforms, B2B platforms are more likely to:

- Launch with standalone value.
- Launch with no same-side value.
- Focus on one specific industry.
- Change the mix of their platform investment over time, offering more cross-side value, and in pre-competitive areas, same-side value.

We also expect, although do not observe directly in the data, that B2B platforms will (1) need to offer compensation to participants for aggregated data and (2) require backing by industry consortia to succeed.

Finally, we craft formal hypotheses based on these insights to serve as the foundation for a proposed agenda for future researchers. We believe that there is a need for understanding the dynamics of platform investment in the B2B space through (a) formal dynamic modeling and (b) longitudinal empirical studies.

Our work is organized as follows: Section 2.2 reviews the developing literature on B2B platforms. Section 2.3 adapts a new framework for analyzing value creation in these settings. Section 2.4 shows the benefits of using this framework by applying it to a dataset of B2B startup platforms. Section 2.5 presents hypotheses for differences revealed by applying the framework to B2B platforms in general, particularly those that impact dynamic behavior over time. Finally, Section 2.6 concludes with potential implications for management and an agenda for future research.

2.2 Motivation and Prior Literature

A comprehensive view of the platform literature is well beyond the scope of this essay. However, to give a quick definition, we refer to (Eisenmann et al., 2011) who provide the following description: “In traditional manufacturing industries that rely on long-linked technologies (Thomson, 1967), bilateral exchanges follow a linear path as vendors purchase inputs, transform them, and sell output. By contrast, platform exchanges have a triangular structure. Users transact with each other, and they simultaneously affiliate with platform providers.”

For a more in-depth treatment, there are a number of surveys that can serve as points of departure for readers not already familiar with the field, including Gawer (2014), Parker et al. (2016), Jacobides et al. (2018), and Kretschmer et al. (2022). To bound our review, we focus more narrowly on the academic literature that treats the B2B sector. To date, coverage of B2B platforms is sparse as compared to B2C platforms but appears to be growing.

In the POM journal, we see several related research threads. Early on, there were papers that explored B2B enterprise resource planning (ERP) systems. These are an important category since successful deployments rely so heavily on external partners. For example, SAP is a major ERP vendor that has hundreds of thousands of external developers who deploy their systems as well as build customized solutions on top of their platform (Iansiti and Lakhani, 2009). Earlier POM researchers focused on the adoption and impact decisions that lead naturally to a broader discussion of platforms that explicitly coordinate external ecosystem partners. For example, (McAfee, 2002) analyzed a natural experiment and showed that firms that implemented ERP systems improved on critical operational metrics such as lead-times and on time delivery percentages. Stratman (2007) explored the adoption of ERP and found that those firms that made investments to improve internal operations gained more benefits from their ERP investments than firms that hoped for improvements in external supply chain performance. A paper from Buhman, Kekre, and Singhal (2005) calls for research that we believe aligns with our view of the role of B2B systems and their evolution to platforms: "The proposed operations management research focus is one that embraces a more holistic view of an "extended enterprise" which involves working with a new business model —the organization as a network. This methodology starts by treating the organization as a system that is enabled by information technology and is characterized by ubiquitous information sharing across traditional enterprise."

Another thread of POM research addresses B2B business in the context of auctions. For example, Mithas and Jones (2007) explore the use of reverse auctions in B2B procurement systems. They find novel results that are directly relevant to our discussions here. Specifically, they note that "Although we found some similarities in empirical findings across the B2B and B2C contexts, we note that some of the empirical regularities observed in the B2C context do not extend to the B2B context. For example, we find that bid decrement and auction duration have no effect on buyer surplus in the B2B context."

A more recent thread of POM research addresses platforms directly by analyzing some of their critical operational decisions. For example Bhargava, Kim, and Sun (2013) model the launch timing and version decisions platforms must make. Anderson and Parker (2013) model the decision for a firm to enter a market in which complementary technologies exhibit strong learning effects and the trade-off between spreading investment across multiple possible solutions or concentrating on one solution. More recently, Guha and Kumar (2018) focus on the critical emerging area of the use of “big data” in operations, information systems, and healthcare. Anderson et al. (2022a) is a rare example treating physical platform relationships. The authors examine the role of 3rd party complementors in the battery electric vehicle industry, such as fast-charging stations and modular product designs.

The majority of current B2B platform research has focused on classifying startup platforms in the B2B sector. Many of these have examined companies in the German *Mittelstand* (small and medium manufacturing companies). Examples of different classification schemes of varying complexity abound, though most have focused on data gathered through interviews, in the very early launch stages (Abendroth et al., 2021; Berger, 2018; de la Boulaye et al., 2019; Kraft et al., 2021). Berger (2018) looks at the growth and evolution of B2B marketplace business models and identifies four different business strategies that have emerged: “one-stop shop”, distribution channel extension,” “procurement network”, and “business model transformation.” These authors offer their perspective that the share of B2B commerce in Germany will continue to grow rapidly, if unevenly distributed among different sectors, and predict that the first areas to develop will be in the manufacturing and automotive industries.

Other classifications and taxonomies have been presented, including de la Boulaye et al. (2019) who look at the potential impacts of online marketplaces on indirect procurement. They identify four types of marketplaces; product focused marketplaces (e.g., for office supplies, equipment), time and materials marketplaces (e.g., for freight services, travel, IT); scope of work marketplaces (e.g., for services such as marketing, telecommunications, utilities); and corporate spinoff marketplaces (e.g., formerly captive platforms that companies developed for their own supply networks). Kraft et al. (2021) look at new business models in Industry 4.0. Their classification includes Digital Refinements of Products and Services; Intelligent and Connected Operation and Production (Smart Factory); New Business Models through Connected and Intelligent Products and Services; and New Business Models through Intelligent Networking of Market Players in a Business Ecosystem. Though useful, these different classifications are not grounded in theory, and can be prone to ambiguities, because the different states are not mutually exclusive and collectively exhaustive (MECE).

The literature that looks at ecosystem complementors, and B2B platform competition is even sparser. (Hein et al., 2019) analyze B2B platform co-creation practices via case studies in the IoT platforms and find that B2B platforms cannot rely on 3rd party developers for value creation as much as B2C platforms can. Instead, they focus on the integration of complementary assets to encourage the supply side, platform readiness for the demand side, and servitization through application enablement to connect supply and demand. Pauli et al. (2020) instead focus on understanding the drivers of complementor adoption in early-stage ecosystems. While they argue that complementors are a key source of advantage for platform business models, their findings show that in the early stages, few complementors are really offering solutions that take advantage of the platform business model, and instead are mostly focused on customized solutions. They highlight the importance of the existing relationship between a platform sponsor and a potential in the adoption decision.

In one of the largest case studies published, Koenen and Heckler (2020) look at 79 different B2B platforms developed and offered by German companies, as commissioned by the Bundesverband der Deutschen Industrie (BDI) (author translation - The German Federal Association of German Industry).[2] They identify that no dominant position of individual platforms can be identified, but that there is competition between platforms with similar offers, and between platforms and more traditional offerings. They note that platforms in the industrial environment are often highly specialized in specific, narrowly defined fields of application or industries. On B2B platforms, there is significantly less asymmetry between platform operators and platform users. Thus, users of B2B platforms can negotiate customer-specific contracts with the platform's operators. Operators of B2B platforms are strongly focused on providing platform users with solutions tailored to the needs of individual users.

Koenen and Heckler (2020) first classify the B2B platforms into 2 categories: data-centric platforms, and transaction-centric platforms. Data-centric platforms are subdivided into Industrial IoT (IIoT) platforms (dealing with preventive maintenance, process optimization, big data analytics) and Data (transaction) platforms: focused on business processes, product data, and cloud. Transaction-centric platforms are subdivided into Marketplaces, Retail and Manufacturing platforms (such as those dealing with Agile Manufacturing or focused on retail and marketplaces); Supply Chain Management and Logistics Platforms (for example in transportation management), and Networking Platforms (for cross company collaboration).

On the other end of the spectrum, in terms of classification complexity, Abendroth and co-authors (2021) set out to identify a new taxonomy for describing B2B co-creation platforms. They identify three essential distinguishing properties, which they label: value creation, platform architecture, and actor ecosystem. Ultimately though, they further subdivide each into 17 dimensions, and further break those down into 71 different categories. They then use the BDI database to code for descriptions. Although ultimately complex and allowing for differentiation, the fact that most B2B platforms studied are at early

[2] https://dih.telekom.net/wp-content/uploads/2019/10/2020-07-German-Digital-B2B-Platforms.pdf

stages of launch complicates matters, as the classification scheme ultimately codes most of the data into catch-all buckets. Other authors have focused on the tradeoffs between “horizontal” and “vertical” approaches to integration (Schermuly et al., 2019), or understanding the attractiveness for complementors to join an existing platform (Pauli et al., 2020), but have done so in narrow case studies in the Industrial Internet of Things (IIOT) settings.

As we hope the complexity of our description of the literature above demonstrates, we believe there is a need for a unifying theoretical framework to organize the different classifications.

2.3 The Need for a New Lens

The classifications described above have significant merits and the authors have done valuable work to open a new literature. However, we find the classifications to be either too general and thus ambiguous, or too specific, and thus difficult to generalize into insights that can guide managerial actions. For example, take the case of a “Data Transaction Platform” that can be both “Data Centric” and “Transaction Centric.” This raises the questions of when is a platform a marketplace versus a data-marketplace? What happens to a transaction platform that also sells aggregate data? These overlaps can be difficult to parse.

Our goal is to extend these efforts by developing a classification/clustering method that is grounded in theory and builds from primitives. We will also connect the way that value is created to specific supply chain linkages. An additional point is that the existing classifications are static rather than dynamic (Anderson et al., 2022b). That is, the schemes mostly rely on a snapshot of the firm today, and then categorize it. We think there is an opportunity to identify potential future paths for the industry through a dynamic approach.

As we have seen above, most of the extant academic literature in the B2B space has looked at data sets that include platforms/companies that are at an early stage in their development. This presents a two-fold problem. On one hand, there are selection and survivorship biases limiting the availability of companies that can be studied, the data that can be gathered, and the conclusions that can be drawn. As such, the space has been dominated by IIoT and Industry 4.0 companies, with their narrower characteristics of how platforms operate. On the other, it’s more difficult to consider alternative scenarios for how the growth paths will unfold.

Schermuly et al. (2019) distinguish between two previous streams of research that, they argue, take on different perspectives: a market-oriented perspective, where the platform is mainly an intermediary between two or more sides in a market, and a technology-oriented perspective that studies platform architectures and the firm's capabilities to facilitate value co-creation and promote innovation. Their use of "platforms" combines both perspectives. This is consistent with a broader framework that we propose, that looks at the sources of value creation and that has been used to understand B2C platforms and the demand side economies of scale that can be created via network effects (Parker et al., 2016).

2.3.1 The Value Creation Lens

By taking again a broad view of platforms as intermediaries in matching markets, we offer a rich, dynamic perspective that includes feedback and can leverage a mapping of the system structure to infer behavior. Formally, we can consider platforms as businesses based on enabling value-creating interactions between external producers and consumers by providing the open infrastructure and setting the governance conditions (Parker et al., 2017). Their aim is to attract and efficiently connect two different sides of the market (e.g., supply and demand; sellers and their buyers; developers and their customers; providers and their clients). The platform sponsor is often a third party that sets the governance structure (rules for trading) and collects a fee for facilitating these matches and enabling transactions (Eisenmann et al., 2009). Ultimately users on either side of the market (complementors and consumers) can derive value through any of three distinct reinforcing feedback loops that connect the ecosystem.

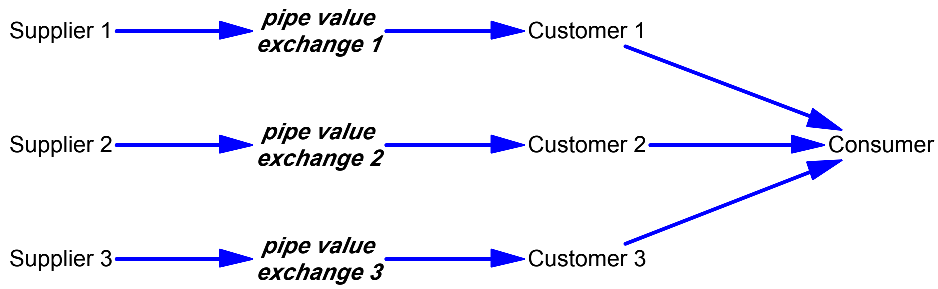
This Value Creation Framework separates the total value for users on either side of the ecosystem into 3 components: stand-alone value, same-side value, and cross-side value.

$$User\ Value := V_{SA} + V_{SS} + V_{CS}$$

The first component is the "*standalone value*" of the platform absent any network effects. For example, a smartphone's standalone value is its use as a telephone, its ability to text, and its camera. None of this value depends on any other participants on the platform. The second is the "*same-side value*," that is the value of other participants on the same "side" of the platform. For example, social networks such as Facebook create value to participants primarily by connecting them with other participants like themselves, i.e., their "friends." The third "cross-side" value is the value to participants of third-party providers on the other side of the market. For a smartphone, owners derive much of their value from the 3rd-party providers of applications (apps).

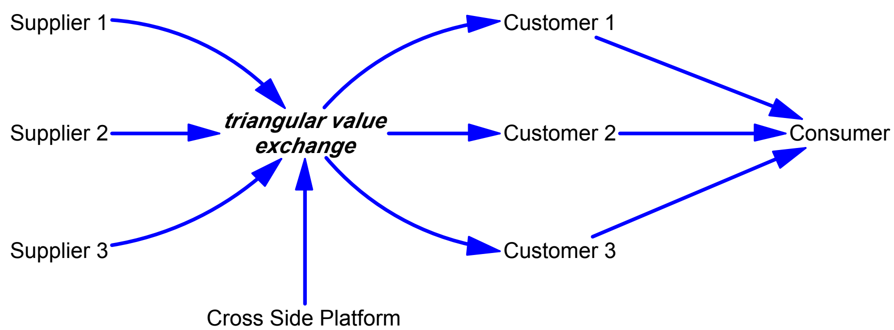
The following figures will help to illustrate some of the complexity of B2B platforms and their multiple echelons. We focus first on standalone value that a typical linear supply chain structure delivers.

Figure 2.1.1: Standard structure with SA value delivered by linear value chains serving an end consumer



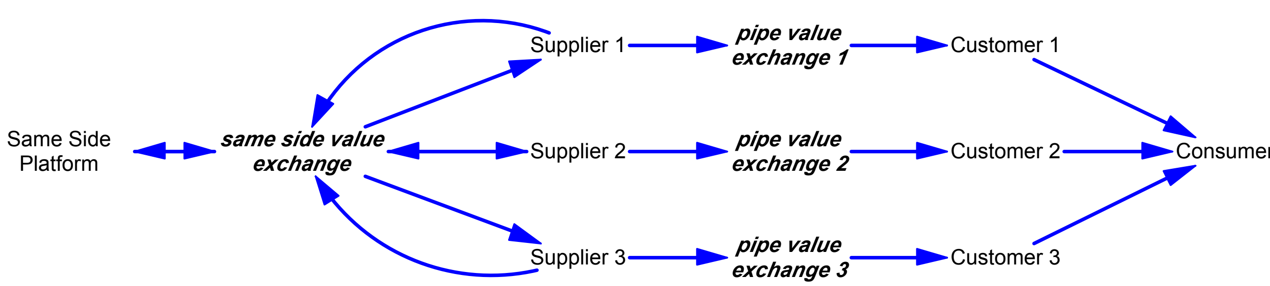
The figure above depicts a traditional linear value chain (pipeline supply chain).

Figure 2.1.2: B2B platform CS value serving downstream linear value chains that serve an end consumer



In the figure above, upstream supply chain value is created by ecosystem partners that work across a platform, e.g., a marketplace.

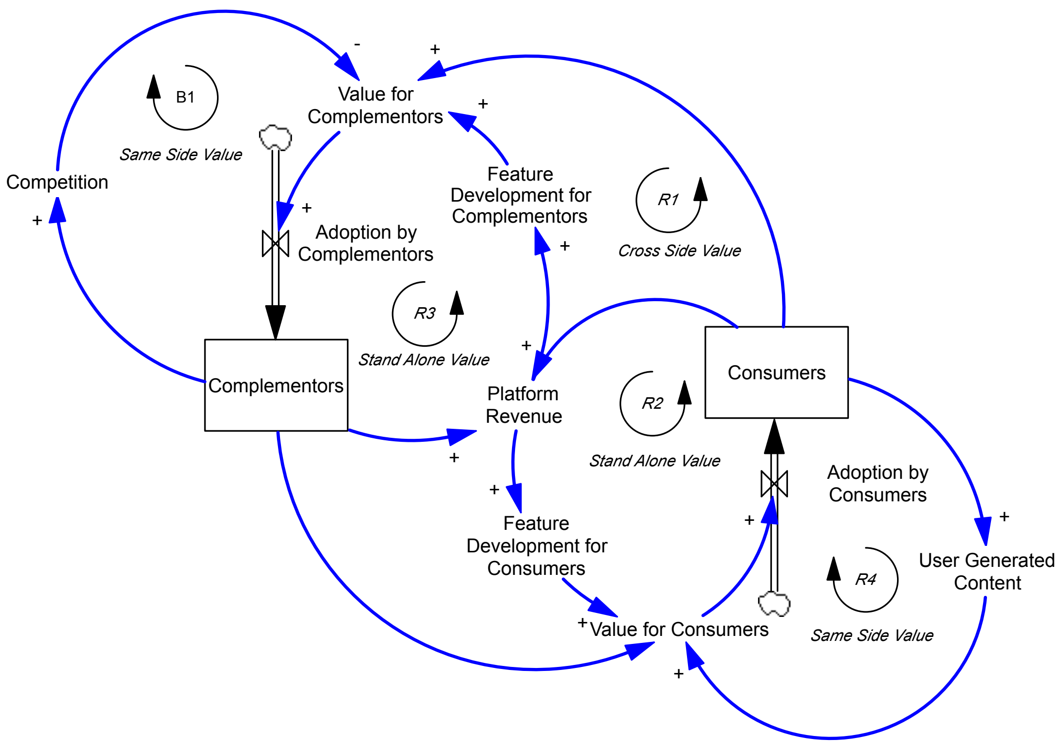
Figure 2.1.3: B2B platform with SS value serving downstream linear value chains that serve an end consumer



In the figure above, upstream supply chain value is created by suppliers that provide same-side value to one another through their affiliation with a platform. That value then gets transmitted through additional supply chain echelons until it reaches an end consumer.

Importantly, the values of each of the three value components may change over time. For example, the relative value of each of the three bins may be very different for a startup than when it becomes a mature firm. Importantly, this framework also allows for insights into the differences that separate B2B from B2C platforms. An illustration is provided in Figure 2.2 below. Note that the externalities depicted in the loops above can be positive (here labeled as reinforcing loops), or negative (here labeled as balancing loops).

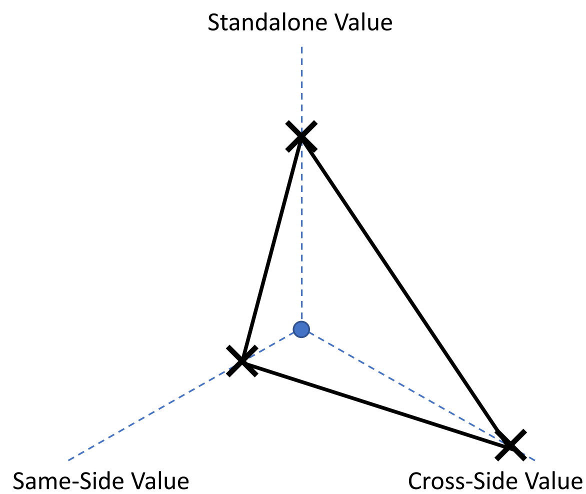
Figure 2.2: Main feedback effects that drive platform growth and attractiveness



Note that, in the figure above, all network effects and externalities can be positive or negative

A graphical way to represent the value of a platform at any given time is by using a “radar chart,” as shown in Figure 3. Each of the three axes in the chart represent the degree of each of the three types of value creation that a platform might offer. As an example, Figure 2.3 presents a radar graph of an example platform, which we will call PlatCo. From the diagram, we can see that PlatCo provides a great deal of cross-side value to the consumer. It also provides a moderately high standalone value. However, its same-side value is minimal. Hence, its value bundle is very much weighted towards the cross-side value provided by participants on the other side of the market.

Figure 2.3: Radar Chart Depiction of a Platform's Value Components for PlatCo



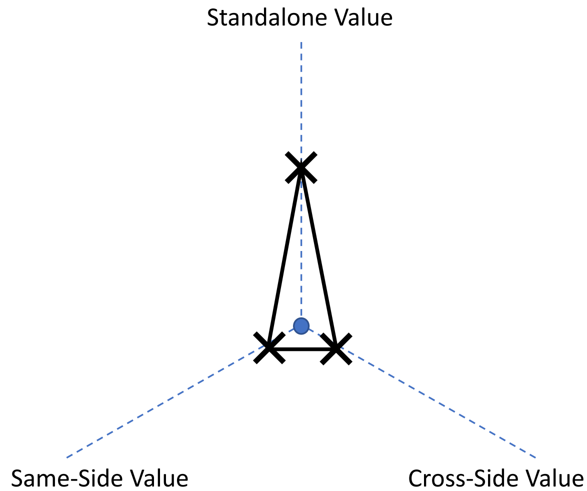
Here "cross-side" value refers to the value of one additional user on the "other side of the platform." To illustrate this, consider a stock of *Complementors* (potential sellers, or 3rd party developers on the platform), and a stock of *Consumers* (potential buyers on the platform). All else equal, more suppliers will join the platform if the perceived *Value for Complementors* increases. Refer to Figure 2 and assume that the system is in equilibrium (where the stocks of *Complementors* and *Consumers* are constant), and then suppose an external shock that, for example, drives up this perceived *Value for Suppliers*. Now, the complementor *Adoption Rate* will go up, and this will result in an increase in the *Complementors* stock (the number of suppliers currently available to sell on the platform). Next, from the point of view of potential consumers, having additional suppliers on the platform increases the perceived *Value for Consumers* (as it increases the probability of a match). This increases *Adoption by Consumers*, which will result in an increase in the *Consumers* stock. That is: from the point of view of a supplier, it is generally positive to have additional consumers (or potential product adopters) on the platform, and from the point of view of the consumer, it is generally positive to have additional suppliers on the platform (or potential sellers). This is reinforcing loop R1.

We can follow a similar reasoning, to derive the "same-side" value, and note that these externalities can be both positive (as is reinforcing loop R4), where the marginal value for a consumer of having one additional buyer join the platform can be positive if user generated content such as recommendation or reputation building mechanisms can reduce serve to reduce search costs, or negative (as is balancing loop B1), where the marginal value for a supplier of having one additional seller on the platform is reduced through additional competitive pressures.

And lastly, we can consider the cases where platform sponsors can choose to reinvest some of the revenue generated in developing extra features on the platform that will increase attractiveness for one (or both) side(s) of the market. These are reinforcing loops R2, and R3. Overall, it is this structure of the system that drives the observed behavior of adoption for network platforms. Conventional wisdom, and the academic literature will say that it is generally beneficial for complementors (supplier businesses) and consumers to join platforms—the larger, the better—because the value to both sides is positive in most cases in the B2C world. However, these increasing returns to scale may be harder to achieve in the B2B world.

Importantly, the strength of these main components of a platform's value creation proposition will shift over time, depending on the platform sponsor's resources, and their growth stage. This is illustrated with an example below. As described earlier, not only may the three sources of value change in absolute terms over time, but the relative value of each might also change. For example, PlatCo as shown in Figure 3 is a mature platform. In comparison, consider Figure 4 below, which depicts PlatCo when it was a startup. Note that it provides less value along all three dimensions than as a mature firm. What is even more important, however, is that the relative contribution of those values is dramatically different. As a startup, Figure 4 shows that Platco provided primarily standalone value and very little in the way of cross-side or same-side value. Only over time, once it had achieved traction presumably, did it begin to invest in creating cross-side value.

Figure 2.4: Radar Chart Depiction of PlatCo as a Startup



2.4 An Application to Data

To show the potential usefulness of the Value Creation Framework described above, we apply it to the BDI database (Koenen and Heckler, 2020) as this is one of the most complete resources to be found in the literature. Through detailed interviews, the BDI database's researchers categorized the emerging B2B platforms of 79 companies into 5 distinct categories. They concluded that, for the B2B platforms in their sample, no dominant position of individual platforms could be identified. Rather, they identified extensive competition between platforms with similar offers, and between platforms and traditional non-platform-based solutions.

We conducted two independent classifications on their dataset, identifying the main sources of value creation for each of the 79 case studies in the sample. We also identify cases where the platform is industry specific, vs open, and where the sponsor is a participant (which can be important for trust and adoption in the B2B setting). Gwet's test for inter-rater reliability, shows a degree of agreement of 83% between our independent coding, which increases confidence in the classifications (Gwet, 2014).

Table 2.1 below, shows a summary of their classification scheme, and highlights some of the reasons that drive the conclusions that B2B platforms are highly specialized in specific, narrow fields of application (Koenen and Heckler, 2020).

Table 2.1: Application of The Value Creation Lens

Platform Classificiation	Total Examples	Examples Creating Value In			Industry Specific
		Standalone Value	Same-Side Value	Cross-Side Value	
IIoT	**23** (29%)	**23** (100%)	**3** (13%)	**9** (39%)	**10** (43%)
Data (transaction)	**13** (16%)	**11** (85%)	**4** (31%)	**13** (100%)	**6** (46%)
Marketplaces, Retail and MU Platforms	**20** (25%)	**9** (45%)	**0** (0%)	**20** (100%)	**16** (80%)
Supply Chain Managemetn and Logistics	**10** (13%)	**7** (70%)	**0** (0%)	**5** (50%)	**5** (50%)
Networking Platforms	**13** (16%)	**7** (54%)	**4** (31%)	**10** (77%)	**6** (46%)
Total	**79** (100%)	**57** (72%)	**11** (14%)	**57** (72%)	**43** (54%)

Table 2.2 below, takes a different tack and summarizes the number of platforms that create value through a "pure-play" that does not involve offering other types of value.

Table 2.2: Pure-Play Platforms in our Sample

Platform Classificiation	Total Number of Platforms by Category	Platforms Relying Soley on Externalities				No Externality (Total Standalone Value Only)	Externality Buttressed by Standalone Value
		Same-Side Only	Cross-Side Only	Cross-Side & Same-Side (No Standalone Value)	Total Externality-only Platforms		
IIoT	**23** (29%)	**0** (0%)	**0** (0%)	**0** (0%)	**0** (0%)	**11** (48%)	**12** (52%)
Data (transaction)	**13** (16%)	**0** (0%)	**0** (0%)	**2** (15%)	**2** (15%)	**0** (0%)	**11** (85%)
Marketplaces, Retail and MU Platforms	**20** (25%)	**0** (0%)	**11** (55%)	**0** (0%)	**11** (55%)	**0** (0%)	**9** (45%)
Supply Chain Managemetn and Logistics	**10** (13%)	**0** (0%)	**3** (30%)	**0** (0%)	**3** (30%)	**5** (50%)	**2** (20%)
Networking Platforms	**13** (16%)	**1** (8%)	**3** (23%)	**2** (15%)	**6** (46%)	**2** (15%)	**5** (38%)
Total	**79** (100%)	**1** (1%)	**17** (22%)	**4** (5%)	**22** (28%)	**18** (23%)	**39** (49%)

Standalone Value

Examining Tables 2.1 and 2.2, a great majority of platforms (72%) create standalone value. On the other hand, Table 3 reveals that only a minority deliver only standalone value without any externality-driven value (23%). Hence, half of the platforms in the sample are in effect externality platforms buttressed by standalone value. On the other hand, if one examines the digital platform firms in the top 100 firms by market capitalization, the pattern is substantially different.3 For example, Alphabet now has Google Suite which drives substantial same-side value through collaboration tools, but that is recent relative to their search offering that was dominant for years. Alphabet's appeal to consumers derived from its investment in search and its revenue growth was primarily dependent on cross-side externalities through advertising. Microsoft, Apple, Amazon, and Tencent relied on standalone value during their growth, but there was always a network component to their growth. Oracle is an exception, but it does not face consumers and has also relied to a certain extent on externalities. In contrast, Salesforce relied mostly on standalone value for its launch and initial growth and only after it had gained significant market traction did it open up to developers to build on top.

Cross-side Value

Many platforms in the sample create cross-side value (72%). However, they generally do so in conjunction with also creating some other sort of value, generally same-side value.

Same-side Value

Relative to the number of platforms creating standalone value (72%) and cross-side value (72%), those creating same-side value represent only a small percentage of the sample (14%). One might expect more given that Meta, Apple, Microsoft, and Adobe relied strongly on same-side value creation. Amazon, Alphabet, and Netflix also relied on same-side value via a customer review system, albeit to a lesser extent.

Industry Specificity

Half of these platforms are targeted towards use by a single industry such as aviation, 3D-printing (additive manufacturing), or even wood-products. This also stands in contrast to the large B2C players who, with potentially exception of Netflix, are agnostic with respect to consumer demographic.

[3] https://www.platformeconomy.com/blog/wert-der-top-100-plattformen-steigt-auf-15-5-billionen-dollar

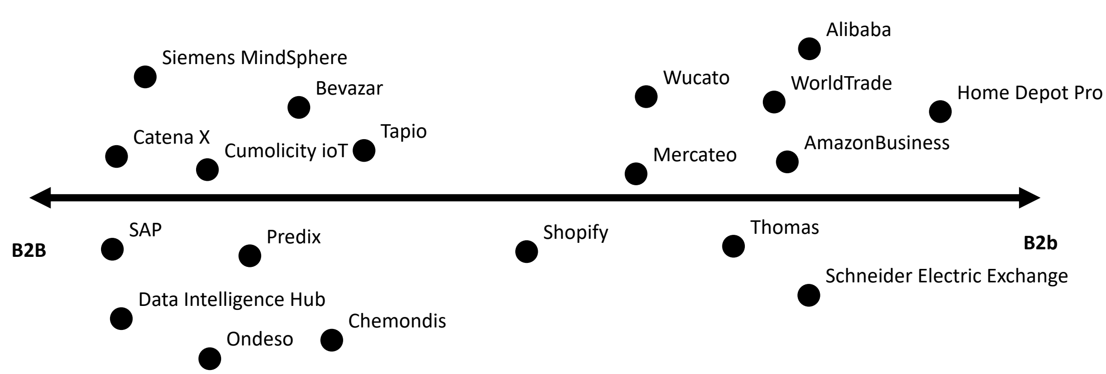
Potential Causes

What explains the different investments in value between the BDI sample and the top-100 platforms just discussed? Of the top-100 platforms? The key may be that the only ones that heavily relied on standalone value only for growth–Oracle and Salesforce–were *not consumer facing.* The others relied heavily, if not exclusively, on consumers for their growth. So, having business as customers versus consumers seems to be different.

2.5 Hypotheses

There are several differences between B2C and B2B that drive the observations in Section 4. We now explore these in detail and create formal hypotheses to summarize our understanding and make predictions. First, we need to make an important distinction. Businesses differ from consumers along many dimensions including operations, organizational structure, and the intensity of the competition they face. Hence, the nature of their supply chain links with suppliers also differs. Some businesses, such as home remodeling contractors relate to their suppliers such as Home Depot much like consumers. Others, like Volkswagen's relationship to Robert Bosch or American Airlines' relationship with Boeing are very different. These different supply chain relationships are reflected in their platform structures. The trade press distinguishes between "B2b" and "B2B" to capture these differences. B2b platforms and supply chains closely resemble B2C. On the other hand, B2B platforms are very different. However, this is not a binary difference, but rather platforms exist along a continuum as shown in Figure 2.5.

Figure 2.5: Business to Business Platforms, From Big "B2B" to "B2b"



Platforms closer to the "B2B" end of the axis above have participants on both the supplier and customer sides of their platform with more complex operations, more sophisticated organizations, and more intense competition than "B2b" platforms' customers, whose characteristics are similar to those of consumers in a "B2C" context.

With this in mind, we next examine the differences between B2B and B2C, such as difficulty in achieving scale and weaker network effects. The result is that managerial approaches that have been successful in a B2C context—gaining rapid scale, building network effects, leveraging lock-in—will be less effective in B2B, requiring different value creation strategies.

2.5.1 Operational Complexity

As noted above, businesses as customers are fundamentally different from consumers. Businesses are inherently much more complex in their requirements for functionality than are consumers, even internal to the "organization." This can easily be seen in the IIoT sector. The complexity of, for example, determining the optimal patterns for predictive and preventive maintenance or coordinating the production of equipment in a factory with perhaps hundreds of machines or fleets of airlines with hundreds of airplanes is simply not found in a household environment. External to the organization, businesses as customers have more complex demands than do individual consumers and much of this complexity is supply chain related. For example, an automotive assembly plant needs components approximately 3000-5000 suppliers to build a car, and if any of those components arrive more than a couple of hours late, the lack of parts will shut the plant down. Contrast this with a consumer's transactions on Amazon, in which there may a few size or color options for a product and 3-4 shipping speeds, or with Facebook, where a consumer uploads and reads content. The result is that relationships between B2B customers and their suppliers are more intricate in structure than those of a consumer's and require markedly more coordination effort. The logistics to deliver products to and from a business must also be managed. Hence, the amount of management attention, computational power, and other transaction costs needed to make the organization run is greater than that needed in a consumer context, and the value of a platform that can facilitate coordination will be higher.

Hypothesis 1: The greater the complexity of a platforms' participants' operations, the more likely a platform will create value through standalone functionality.

2.5.2 Organizational Sophistication

At the same time, business purchasing organizations are also much more discerning than consumers and will be less swayed by external influencers. In addition, purchasing, systems implementation, and operations tend to be done by different divisions within an enterprise. Dedicated purchasing organizations benefit less from the use of a platform to reduce search costs. They will also be better able to leverage the benefits of Blockchain and similar technologies, which enable smart contracts etc., without need for a platform. They also better at costing suppliers' offerings. Lastly, purchasing cycles are longer. Between these factors and operational complexity, direct sales will be relatively more useful in a B2B context than, for example, viral marketing. Hence, overall onboarding a business to a platform and supporting it is more expensive for the platform both on the sales and on the technical side. It is very far from plug-and-play. The net result is that the marginal cost of adding an additional customer to a platform will be very high relative to that in a consumer context, in which the marginal cost of participation is essentially zero. It is not enough for a platform that its computer scientists to develop an algorithm and have marketing specialists target consumer demographics. Industry expertise is required to create value for the customer. Industry expertise is also useful from the perspective of the platform's direct sales force, because they will more effectively convince participants to sign on if they understand their business needs.

That said, firms are markedly differentiated by their particular product and market, so industry expertise from one market segment will be of much less value to other segments. Between these two forces, high marginal costs and the fragmentation of industry knowledge, the viability of competing for an individual industry is higher and platforms can gain an advantage from being industry specific. We believe that this accounts for the high proportion of industry-specific firms in our sample.

Hypothesis 2a: The more complex a platform's participants' operations, the more likely a platform is industry specific.

Hypothesis 2b: The more sophisticated a platform's participants' organization, the more likely a platform is industry specific.

As we will see, organizational sophistication has other ramifications as well for B2B, particularly when combined with other factors characteristic of B2B platform participants.

2.5.3 Competition

Unlike consumers, businesses compete with each other. Hence, while participating in a B2B platform, the nature of the externalities may differ. For example, there are in general, all other things equal, fewer businesses than people. Hence, search costs are lower with respect to finding suppliers, and the value of joining a platform for cross-side externalities will be less. This will be particularly true if firms are operationally complex, their needs are differentiated by industry, or their customers' purchasing organizations are more sophisticated. If competition is very high, price visibility and the disclosure of other competitive information on a platform may make marginal costs negative at some point. From a platform perspective, the benefit of offering cross-side value is less. The implication is that there will be fewer cross-side only offerings by platforms.

Hypothesis 3a: The more competitive a platform's participants' markets, the less likely a platform will offer solely cross-side value.

Hypothesis 3b: The more complex a platform's participants' operations, the less likely a platform will offer solely cross-side value.

Hypothesis 3c: The more sophisticated a platform's participants' organization, the less likely a platform will offer solely cross-side value.

2.5.4 Data Governance

Because of competition and regulation, B2B firms are much more sensitive about their data than consumers are. The benefits of sharing information with other organizations may be limited and even if the data itself is not valuable per se, sharing data may inadvertently reveal operating trade secrets or other sources of competitive advantage. Hence, the value of same-side platform participation for businesses is likely to be much less than that for consumers.

Hypothesis 4: The more competitive a platform's participants' markets, the less likely the platform will offer same-side value.

Businesses are more aware of the value of their data in general than are consumers, particularly if their organizations are also sophisticated as described earlier. They are aware of the value a platform obtains from data-driven learning. Hence, even if they are willing to share information, they will be more likely to demand compensation for it from the platforms.

Hypothesis 5: The more sophisticated a platform's participants' organization, the more likely a platform will need to compensate participants if their data is aggregated and sold.

While we did not observe this in our data set, we also expect that over time, these data governance issues will create an advantage for those platforms that are sponsored by a consortium of industry members because of higher levels of trust. For these reasons, General Motors, Tesla, or Volkswagen may try to create their own platforms, but we suspect that they will ultimately fail. Thus, we believe that as the platforms in this data set mature, the percentage of surviving platforms that are sponsored by a consortium will increase and the percentage sponsored by an individual firm will decrease.

Hypothesis 6: Over time the fraction of platforms in a given market segment that are sponsored by industry consortia will increase, and those sponsored by individual firms will decrease.

2.5.5 Dynamics

Platforms are dynamic systems: they launch in one way but will almost surely adapt over time to offer different sources of value to their users. For example, Google is now investing in additional standalone value plus same-side value with Google suite. We can also expect B2B platforms to shift the way they create value over time as they mature. For example, we've seen that the number of potential participants on each side of the market is likely limited in many B2Bs. Hence, market penetration on both sides of the market must be high to create sufficient cross-side value, and to tap into the reinforcing loops driving user adoption. At the same time, the majority of platforms that offer standalone value in our sample is high and the platforms that offer cross-side value without standalone value is limited. However, we would expect as platforms mature from being startups, they will grow their number of participants by tapping into reinforcing loops resulting from externalities. Hence, the potential worth of any platform investment in cross-side value to participants should increase, while the cross-side value remains constant. The result is that the benefits to investing in creating cross-side value should increase faster than that for same-side value, and platforms will invest relatively more in cross-side value and less in standalone value. Hence, we would expect that over time B2B platforms' value propositions will shift from a greater emphasis on standalone value to a greater emphasis on cross-side value.

Data platforms in the sample exhibited cross-side value creation in the BDI startups' descriptions of their value offerings. However, we would also expect that the value of same-side externalities, if it exists, should ramp up over time. One can easily imagine data exchange in pre-competitive areas among industries in the same industry becoming more useful as a platform matures past its startup phase. Hence, we would expect that over time, the relative value of same-side externalities should either remain zero or steadily increase. Hence, investment and offering of same-side value will either remain zero or steadily increase as a platform matures.

Hypothesis 7a: B2B platforms will over time offer a mix of value that shifts from standalone value to cross-side value.

Hypothesis 7b: B2B platforms will over time offer a mix of value that either (a) never offers same-side value or (b) increasingly emphasizes same-side value in precompetitive areas, especially if the platforms already offer cross-side value.

Table 2.3 summarizes the hypotheses as well as the differences between B2B and B2C platforms that drive them.

Table 2.3: Differences between the B2B and B2C Settings

	Business to Business Platforms	Business to Consumer Platforms	Hypotheses
Operational Complexity	• Businesses as customers have more complex demands, requiring more institutional expertise and sales support. • Demand higher reliability (to offset the larger cost of potential downtime for the customer). • Requires coordination of complex and chain activity, which is unforgiving of failures and increases transaction costs. • Requires integration with other electronic solutions and legacy systems in the supply chain.	• Straightforward purchases on the platform requiring little support • Support can easily be automated.	• **H1**: The greater the complexity of a platforms' participants' operations, the more likely a platform will create value through standalone functionality.
Organizational Sophistication	• Customers have dedicated purchasing functions that are more discerning, focusing more on their own analysis of the technical details and costing of an offering, resulting in lower search costs. • Customers can better leverage Blockchain and similar technologies • Customers' sales cycles are longer. • Marginal onboarding and support costs for a platform to add an additional participant are high. • Industry expertise is required to create value for the customer and acquire the customer. • Industry knowledge is fragmented and non-portable between market segments.	• More opportunities for virality, and impulse purchases, affected by word-of-mouth and influencers. • The marginal cost of serving one additional customer is lower, and can approach zero. • Consumer transaction costs are minimal, particularly because of price transparency.	• **H2a**: The more complex a platform's participants' operations, the more likely a platform is industry specific. • **H2b**: The more sophisticated a platform's participants' organization, the more likely a platform is industry specific.

Competition	• Potential customers face strong direct competition from other businesses. • Overall, there is a smaller number of potential participants on either side of the market. • Lower search costs lead to lower value of joining a matching platform. • Price transparency may not be optimal. • Marginal benefit for a participant to join a platform is low relative to B2C or even negative.	• Customers are not in direct competition with one another. • Generally higher number of consumer participants. • Marginal benefit for a consumer to join a platform is high relative to B2B, because there is no competitive crowding	• **H3a**: The more competitive a platform's participants' markets, the less likely a platform will offer solely cross-side value. • **H3b**: The more complex a platform's participants' operations, the less likely a platform will offer solely cross-side value. • **H3c**: The more sophisticated a platform's participants' organization, the less likely a platform will offer solely cross-side value.
Data Governance	• Stronger privacy concerns, as businesses are more aware of the value of their data. • Lower benefits of information sharing with competing organizations. • Trust is highly important. Consortia-sponsored platforms are likely to be trusted more than those sponsored by individual firms.	• Customers are less secretive with their data, and users will be willing to pay with their data. • Less sensitive to data storage and security concerns.	• **H4**: The more competitive a platform's participants' markets, the less likely a platform will offer same-side value •**H5**: The more sophisticated a platform's participants' organization, the more likely a platform will need to compensate their participants if data is aggregated and sold. • **H6:** Over time the fraction of platforms in a given market segment that are sponsored by industry consortia will increase, and those sponsored by individual firms will decrease.
Dynamics	• Cross-side and, especially, same-side offerings create less value for participants, raising the importance of standalone value. • As industry platforms mature overtime, they may shift from pure stand-alone plays, to increase their cross-side effects.	• Requires less market penetration to be successful.	• **H7a**: B2B platforms will over time offer a mix of value that shifts emphasis from standalone value to cross-side value. • **H7b**: B2B platforms will over time offer a mix of value that either (a) never offers same-side value or (b) increasingly emphasizes same-side value in precompetitive areas, especially if the platforms already offer cross-side value.

2.6 Discussion and Conclusions

In this article, we describe a "value creation lens" that brings together elements of both the information systems and the production and operations management literatures, which generally have proceeded largely in parallel. The framework differentiates platforms by the mix of value they create through leveraging same-side externalities, cross-side externalities, and standalone value. We specifically choose these "bins" from information economics, instead of others, because of how they differentially transform the nature of relationships between supply chain echelons and within the firm. We then apply this framework to highlight the differences between business-to-consumer (B2C) platforms and business-to-business (B2B) platforms. A number of differences, including more complex operations, more sophisticated purchasing organizations, more competition, and increased data-governance concerns differentiate the two. The result is that many platform strategies that have been successful in business-to-consumer contexts may not transfer to business-to-business.

To gain insight, we apply the framework to a sample of 79 business-to-business platforms. Because the business-to-business platform industry is more inchoate than business-to-consumers, they are mostly earlier in their life cycles. We find that the platforms are more likely to launch with standalone value and less likely to launch with same-side value. They tend to focus on one specific industry.

Finally, we craft formal hypotheses to explain these differences. We also propose two additional hypotheses that fall out of the reasoning behind the hypotheses. One is that B2B platforms will compensate their participants for aggregating their data and that B2B platforms that are backed by consortia will succeed more often than those backed by individual firms.

The value creation lens affords that investment and ultimately the mix of value offered by a platform may change over time as a platform matures. There is some suggestion of this in the descriptions provided by the platforms in our sample. Moreover, a number of platforms in the BDI sample primarily focus on enabling logistics and inventory management. These platforms are currently *not* facilitating the creation of new matches between firms to create value and thus are essentially providers of standalone value only. That said, many of these startups advertise that their improvements come from standardizing information flows to improve transparency and coordination. This standardization of interfaces between suppliers will reduce the costs for a focal firm to switch from one supplier to another on that platform. Hence, joining the platform will become more attractive for new suppliers and ultimately a multi-sided market will result, creating cross-side value for the platform to the customer. We note that the opposite trajectory, that of a platform like Google offering cross-side or same-side value initially followed later by standalone value such as Google Docs, is much less likely to occur in the business-to-business space, if for no other reason than that business-to-business platforms so often launch with standalone value.

Our work has a number of implications that can guide B2B growth strategies. While traditional B2C platforms can use a variety of pull-strategies to attract customers to either side of the market, in an attempt to jump start adoption, B2B platforms are likely to be more limited in their options to resolve the chicken-egg startup problem. Limited market sizes and the weakened impact of word of mouth on adoption decisions reduces virality. In most of the cases that we have studied, B2B platforms leverage industry expertise and use their own established supply chains to seed the platform.

Importantly, heterogeneity in size and bargaining power of the firms that are potential customers can shift the balance. Reputation effects of a large customer joining the platform can lead to greater visibility and adoption. However, the bargaining power of these large firms may force concessions that could ultimately reduce the attractiveness to others.

Though it seems advantageous to start the platform with an industry sponsor and by bringing in established supply chains, there may be unintended consequences that can ultimately limit growth. Trust issues, lack of transparency, and self-preferencing when the sponsor is also a platform user, as well as data governance, transparency and privacy concerns will be critically important. Additionally, B2B platforms serve more niche markets and still rely on some relationship building. The result is that the advantages of first movers may be more limited, as they are characterized by more customer stickiness and a more fragmented industry. Competition can lead to fragmentation, and it is unlikely that the winner-take-all outcomes frequently seen in B2C will be as prevalent in the B2B world.

In practice, we can see evidence that markets are shifting towards platform centric infrastructures as digitalization increases. At the same time, the literature on B2B platforms is still nascent. As a result, different approaches, from detailed case studies, to leveraging existing theory, to modeling and simulation can yield insights. However, there is a need for an overarching grounded framework that leverages the current understanding of platforms from B2C settings and characterizes the differences in the structure and dynamics of the systems in B2B settings. Another need is a dynamic framework that managers can use to identify the reinforcing loops that will drive adoption and growth and intervene to make them stronger. We propose that the value creation lens provides a beginning of a research agenda to address these issues.

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Chapter 3

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 facilitate 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 may evolve differently depending on market and industrial context.

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

3.1 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. In response 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, information systems, and behavioral operations management to explore how platform firm incentives, competitive pressures, and their current strategy, influence platforms’ decisions to either obfuscate prices, or 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. Our model is generalizable and can be parameterized to provide insights for price transparency decisions in a variety of digital markets, such as: online ticket resale; food delivery; hospitality and airline bookings. 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*.

3.2 Motivation and Prior Literature

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 shows 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 reflect 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).

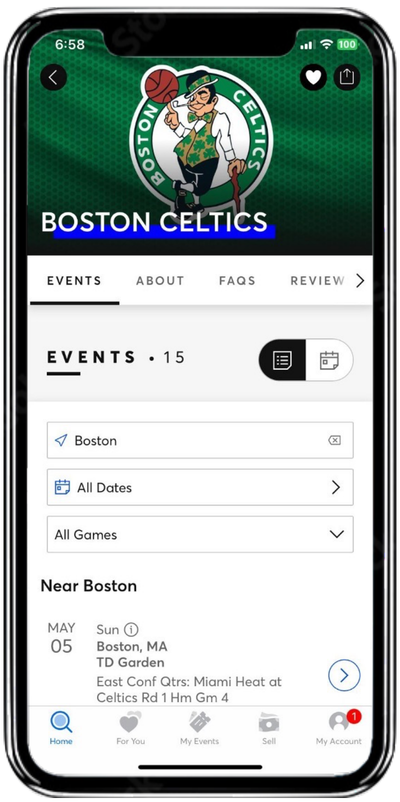
Platforms can increase competition by consolidating price information from multiple firms. To counteract this intensified competition, the complementor firms often employ intricate pricing strategies. However, platforms have some influence over the extent of pricing complexity adopted by firms since 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 3.1 below provides an illustration of price dripping and hidden fees on the largest online ticket reselling platform (*Ticketmaster*). Additional examples of hidden fees from online platforms, including ticket sellers, food delivery, hospitality and ride-hailing purchases are shown in Appendix 3.A.

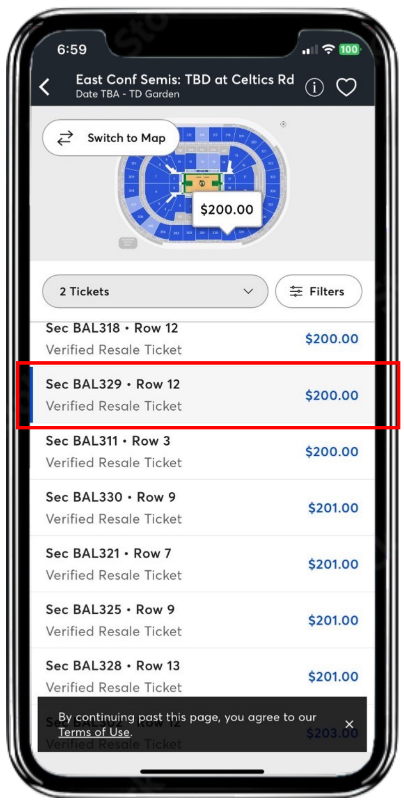
Figure 3.1: Price-Dripping and Hidden Fees on Ticketmaster App.

Fig 3.1.1*



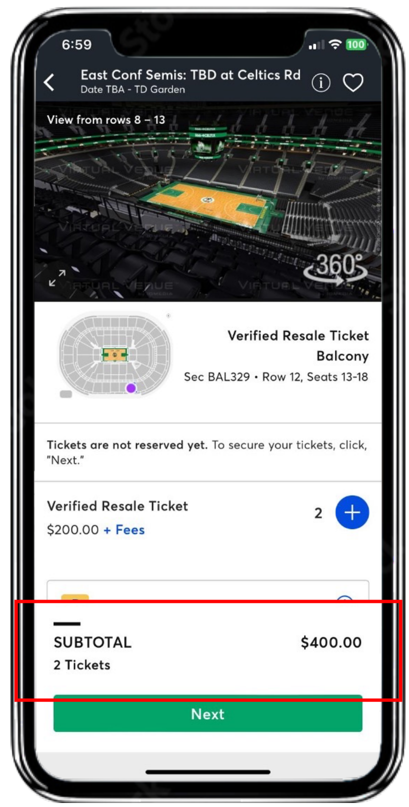
These screenshots correspond to a typical order for resale tickets on Ticketmaster, where Hidden Fees are "dripped on" and revealed only as the consumer progresses through the purchase process.

Fig. 3.1.2



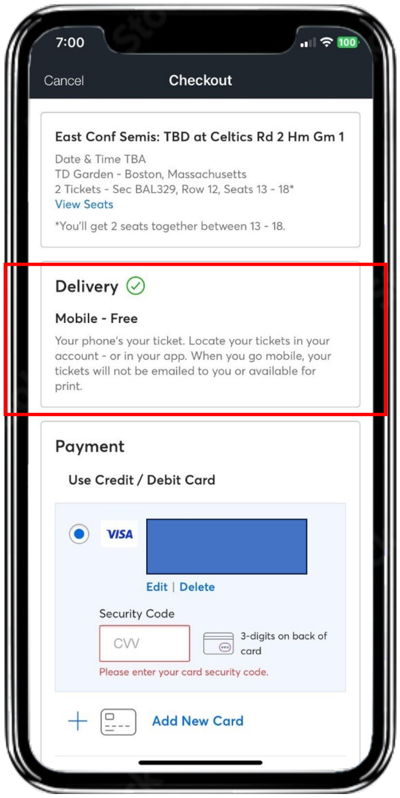
Consumers first observe a listing of potential offerings for different seating locations and prices. In this case, a consumer has decided to purchase 2 tickets for an Initial Visible price of $200/each.

Fig. 3.1.3



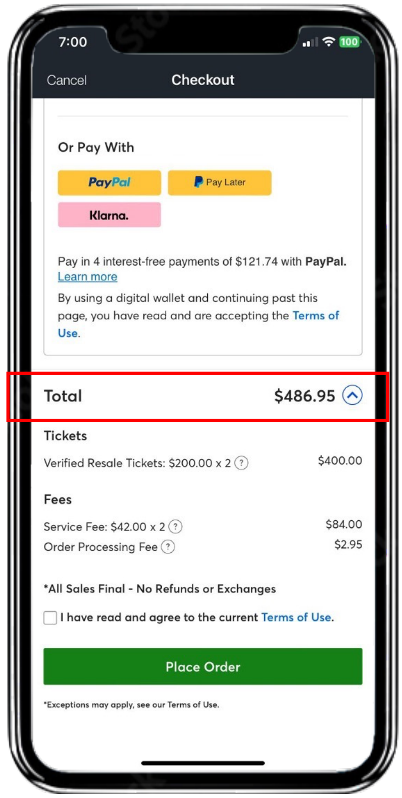
Consumers move through new screens. Notice that there is a small indication that the price is "$200 + Fees" above but hovering over or clicking on the "Fees" provides no additional information.

Fig 3.1.3



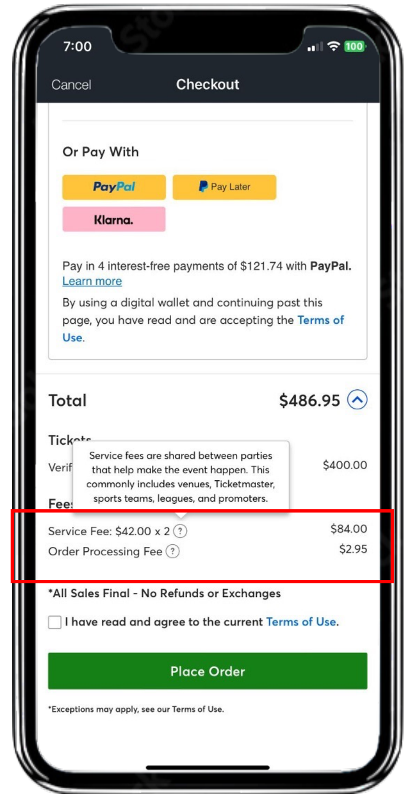
A potential source of additional confusion for consumers is that the following screen indicates that there are no Delivery Fees for mobile delivery.

Fig 3.1.4



However, as the consumer is ready to pay (and importantly after their credit card or payment information has been request, the Hidden Fees are now made visible. In this case, The Total Price has jumped to $486.95 , up from $400.

Fig 3.1.5



Additional information is only revealed by hovering over the 2 line items in the recently disclosed Fees The line for Service Fee reads: "Service Fees are shared between parties that help make the event happen. This commonly includes venues, Ticketmaster, sports teams, leages and promoters. The price for the consumer has increased by 22%.

Figure 3.1.1-3.1.6 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.
*The data were collected on May 1st, 2024

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.

3.3 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.

3.3.1 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.

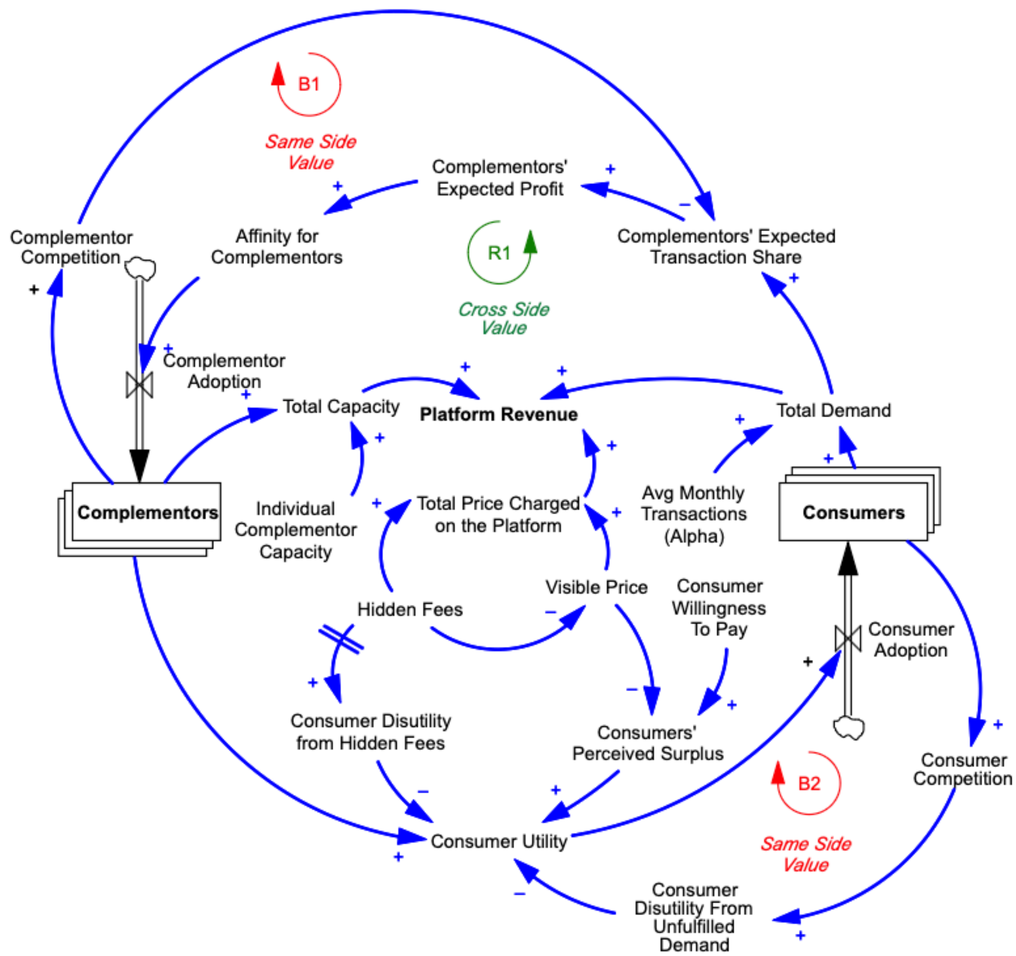
Here, the cross-side value refers to the change in attractiveness provided by having one additional participant on the other side of the market, the same side value refers to the change in attractiveness resulting from one additional participant on the same side of the market, and the stand-alone value 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, both in terms of ease and speed of matching, and in variety of offerings. The same-side value refers to the decrease in utility of having one more competing buyer, which may result in unfulfilled demand

And the stand-alone value refers to a strategic decision that that the platform can make regarding it's pricing and transparency.

Previous work that on platform price transparency has been exploratory (Belleflamme and Peitz, 2019), and has focused on understanding and quantifying the strength of the cross-side network effects. Our work expands on previous models, by explicitly considering the potential negative effects of same-side competition, and the potential for high attractiveness and differentiation that can be derived from stand-alone value propositions, such as the strategic decision to shroud prices or become transparent.

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 3.2 below, that shows the various ways in which a ticket-seller matching platforms can create value around a pricing decision:

Figure 3.2: The Value Creation Lens for Pricing in Online Platforms



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.

3.3.2 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.

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 most 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 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:

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

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.

$MS_B(t)$ represents the percentage of consumer participation on the platform, at a given time. This value for the market share 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. Consumers adopt the platform with some delay τ_B. Thus, the change in $MS_B(t)$, is given by:

$$MS_B'(t) = \frac{\widehat{MS_B}(t) - MS_B(t)}{\tau_B} \tag{15}$$

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 the delay for complementors adopting the platform τ_S. Thus, the change in $MS_S(t)$ is given by:

$$MS_S'(t) = \frac{\widehat{MS}_S(t) - MS_S(t)}{\tau_{SA}} \tag{20}$$

The model's key parameter values are shown in Table 3.1 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 Appendix C and the accompanying model file.

Table 3.1: 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($)	0.6
$p_{visible}$	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
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)	0.2
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

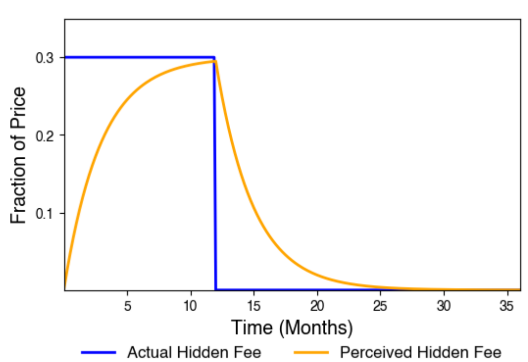
*Parameter Base values have been informed by previous literature on B2B and transaction platforms (Anderson et al. 2022; Koenen and Heckler, 2020; Zhu and Iansiti, 2019). We also draw from Prospect Theory, and account for the fact that loses loom about twice as large as gains (Kahneman and Tversky 1975). Smith and Brynolfsson (2001) also find evidence to suggest that "consumers are approximately twice as sensitive to changes in shipping price and sales tax [which are typically "hidden fees"] as they are to changes in item price.
Importantly, we are not calibrating a model to data, but rather are interested in the magnitudes and ratios of the parameter values.
Extensive Sensitivity Analysis is performed in Sections 4 and 5.

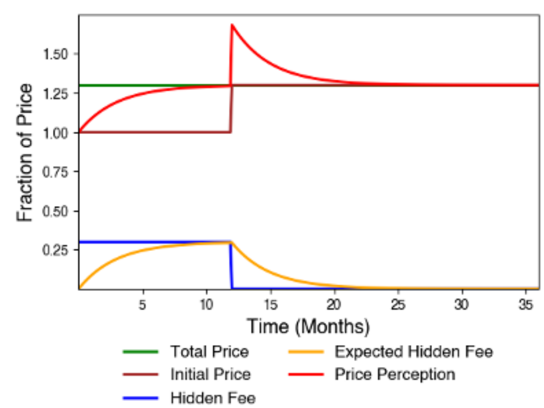
3.4 Simulation Results

3.4.1 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 3.3: 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.

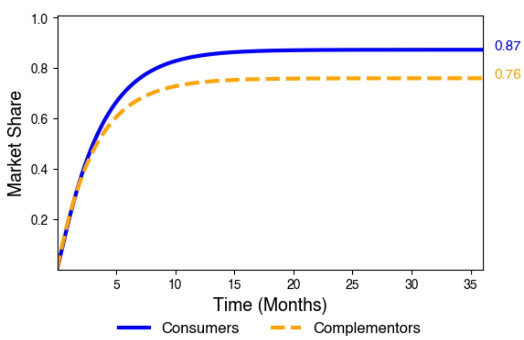
Given enough time and engagement, consumers will become fully aware of the hidden fees, and price it into their decision making. Importantly, price perceptions are "sticky", and if the platform decides to unshroud (drop the hidden fees) and become transparent, consumer price perceptions will remain high 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.

3.4.2 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. We run our model for a simulated period of 3 years. Figure 4 below shows the results:

<table>
<tr><th colspan="2">Figure 3.4: Case 1: Monopoly Platform, Shrouding, No Consumer Learning</th></tr>
<tr><td>



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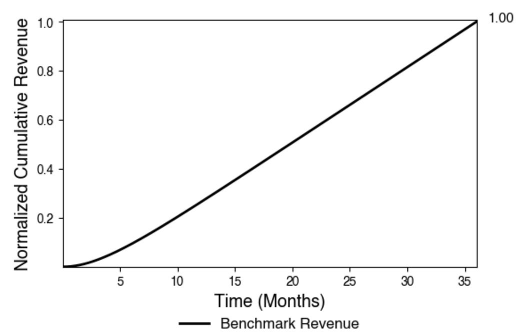
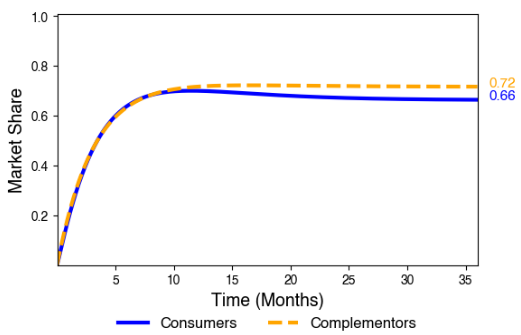


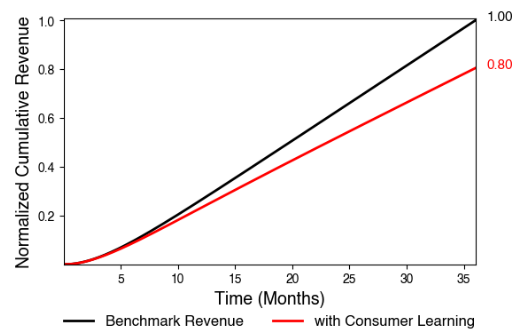
</td></tr>
<tr><td>We plot consumer (blue line) and complementor (orange line) adoption and show the respective market shares. In the monopolistic case, the fraction of consumers and complementors that is not on P_1 finds the outside option more attractive.</td><td>Revenues grow as the installed bases 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.</td></tr>
</table>

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 our illustrative case, Consumers derive a higher Utility $(U_B \approx 1)$ relative to the outside option $\rho_B = 0$. In this scenario, most of the U_B comes from cross-side network effects. We replicate finds from previous studies in this benchmark case where 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 3.5 shows results:

Figure 3.5: Case 2: Monopoly Platform, Shrouding, Introduction of Consumer Behavioral Learning





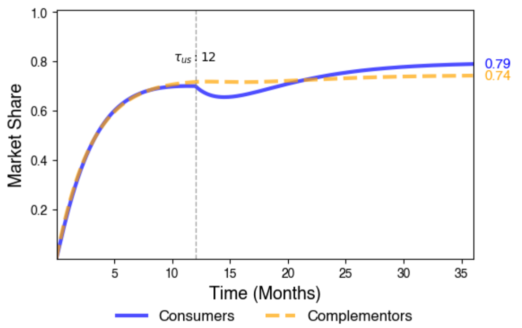
We see that consumer (blue line) market share initially grows, as consumers are "naïve" about the hidden fees. However, we note the growth is slower than for the monopoly case.	We see that total revenues in the case where there is consumer learning (red line) are lower than in the benchmark case when all consumers are naïve.

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 3.4.

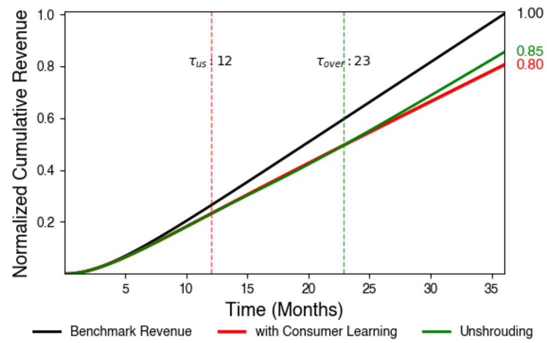
Total revenues are lower than in the benchmark case. This follows from the fact that the platform has a lower installed base of both consumers and complementors, which lowers the transaction volume and ultimately reduces revenues. This is a direct consequence of the fact that a larger percentage of consumers 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 3.6 shows the results:

Figure 3.6: Case 3: Monopoly Platform, Shrouding to Unshrouding, Consumer Behavioral Learning



We show consumers (blue line) and complementors (dashed orange line) for a monopolist that decides to become transparent at τ_{us}=12.



We show cumulative revenues for the new unshrouding case (green line), plotted against the benchmark (black line) and previous case where the platform was always shrouding (red line). Revenues for the shrouding case are higher than for the unshrouding case from τ_{us}=12 to τ_{over}=23

In the beginning, consumers and complementors initially follow a similar dynamic as in Figures 3.4 and 3.5. After one simulated year, at time $\tau_{us} = 12$, 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. These further drives consumer adoption, and the platform can achieve a higher market share than in Figure 3.5.

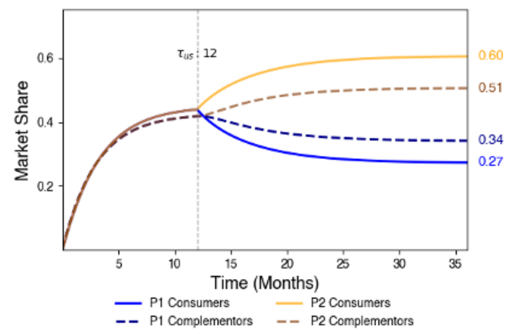
We see that platform revenues (green line) initially fall below the previous scenario (red line) as the installed base is reduced. However, over time, the transparent strategy overtakes the shrouding strategy and becomes more profitable. In this setting, it takes the platform almost 11 months after unshrouding for cumulative revenues to surpass the previous scenario. But because the platform can 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, if 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 if engaging in shrouding is profitable for firms that have enough market power.

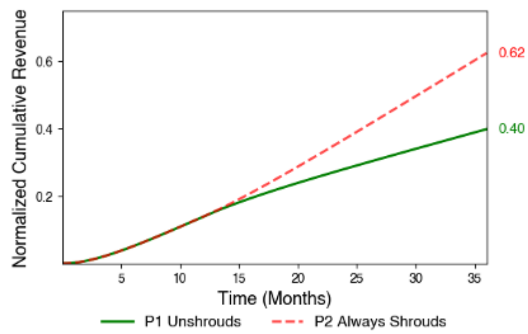
Interestingly, even in a monopoly setting, a platform that has previously been shrouding fees and moves to disclose will face a challenge as it will have to educate consumers about its new price structure. That is, consumers who have previously realized the existence of hidden fees on the platform and 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 $\tau_{US} = 12$.

Figure 3.7: Case 4: Platform Competition, Unshrouding vs. Shrouding, with Naïve Consumers



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.

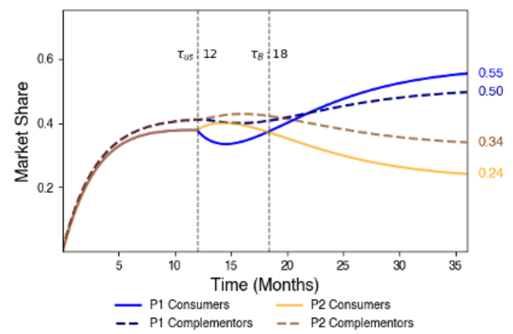


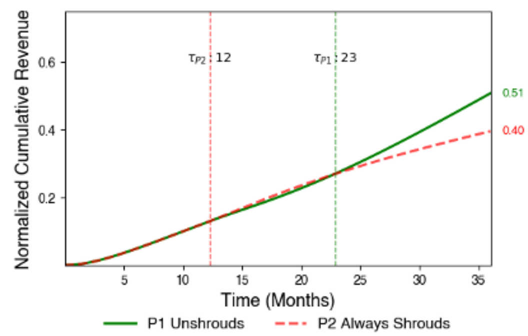
Here, the green line is P_1 revenue, while the red line is P_2 revenue. After P_1 unshrouds, it loses market share while P_2 seems to thrive. Since consumers are not accounting for hidden fees, P_2 wins.

In Figure 3.7 above, when P_1 unshrouds it initially looks more expensive (less attractive) to prospective consumers who have become accustomed to the presence of hidden fees, and as a result it faces a consumer exodus that ultimately also drives away complementors. This loss of market share by P_1 is claimed by P_2. Because there is no consumer behavioral learning, P_1 never recovers. In this setting, shrouding is optimal, and the evidence is shown in the difference in revenues.

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 3.8: 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.

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. 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's shrouding and $P_1's$ transparency. In equilibrium, even though there is no difference in their final prices, consumers prefer P_1 because there is no disutility from being shrouded to

These results are in line with previous 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 (Lee and Han, 2002; Roman 2010). Here, the transparent strategy can pay off. 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.

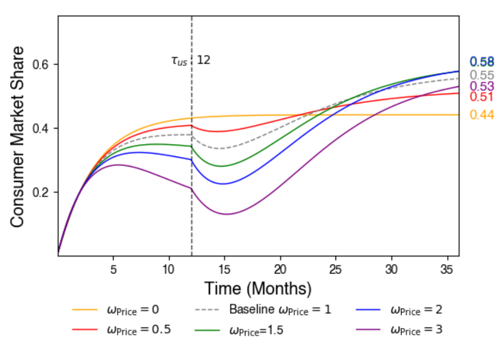
3.5 Dynamics of Platform Competition

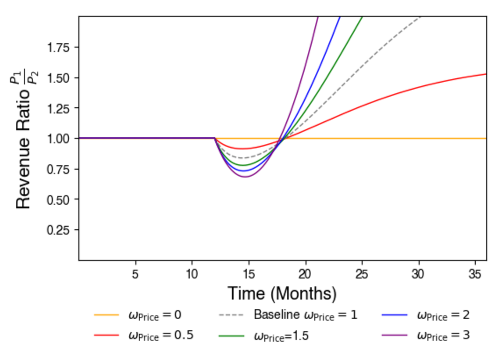
Our base settings have shown that the decision to shroud prices or become transparent depends not only on the current market environment, but on consumer's priors about hidden fees. We recall from Section 3, that we have modeled the consumer's utility as a combination of 4 components: buyers derive increasing 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 3.9 shows these effects below:

Figure 3.9: Effects of Price Sensitivity ω_{price}





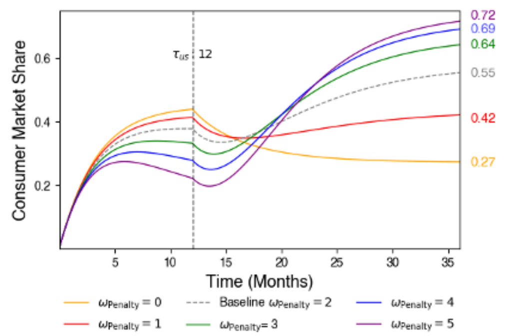
We model increasing values of consumer price sensitivity (ω_{price}), and we focus on the consumer market share for the transparent platform *(MS_{B,P_1})*. Compare outcomes against the benchmark case $\omega_{price} = 1$ in dashed gray above.

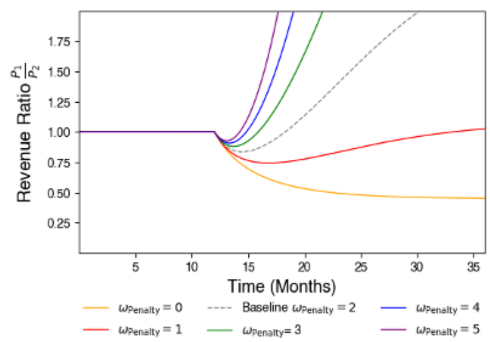
We show the Revenue Ratio ($\frac{Rev_{P1}}{Rev_{P2}}$), as a summary measure of platform firm performance. A Revenue Ratio greater than 1, indicates benefits from transparency for the unshrouding platform P_1. In general, the greater the consumer price sensitivity (ω_{price}), the greater the benefits 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. Evidence from Prospect Theory shows that loses loom about twice as large as gains, (Kahneman and Tversky, 1979; Smith and Brynjolfsson, E., 2001) 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 3.10 shows these effects below:

Figure 3.10: Effects of Coefficient of Disutility of Hidden Fee ($\omega_{penalty}$)





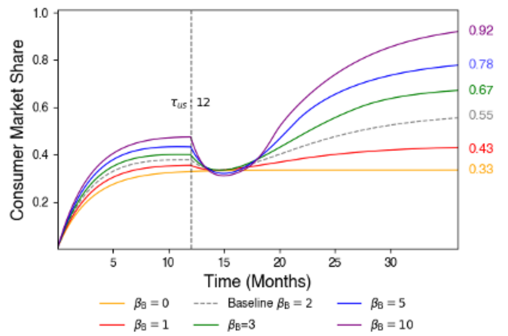
We model increasing values of consumer disutility on hidden fees ($\omega_{penalty}$), and we focus on the consumer market share for the transparent platform (MS_{B,P_1}). Compare outcomes against the benchmark case $\omega_{penalty} = 2$ in dashed gray above

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.

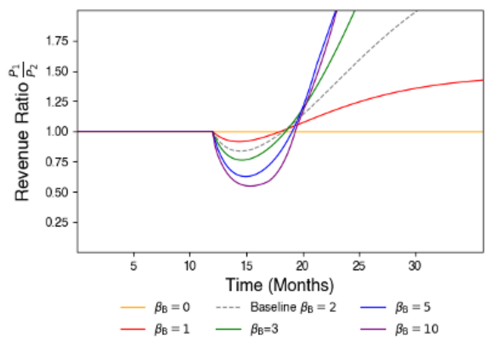
When $\omega_{penalty} = 0$, consumers are completely indifferent to being shrouded to. In this case, it is optimal for platforms to shroud their fees. In fact, whenever $\omega_{penalty} < 1$, the transparent platform underperforms their shrouding counterpart. Notice in Figure 10 that for $\omega_{penalty} < 1$, 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 3.11 illustrates the effects of β_B below:

Figure 3.11: Effects of Sensitivity to Affinity for Consumers (β_B)



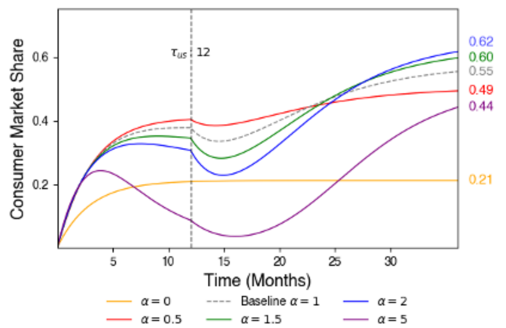
We model increasing values of consumer sensitivity to affinity (β_B), and we focus on the consumer market share for the transparent platform *(MS_{B,P_1})*. Compare outcomes against the benchmark case $\beta_B = 2$ in dashed gray above



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 lack of heterogeneous consumer preferences. 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 initial sensitivity 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 into 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 3.12 below considers the effects of the average transactions desired by each buyer, which we have previously denoted α:

<table>
<tr><td colspan="2">Figure 3.12: Effects Average Transactions Desired Per Month Per Person (α)</td></tr>
<tr><td>
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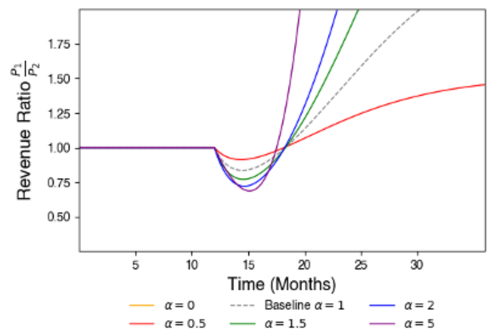
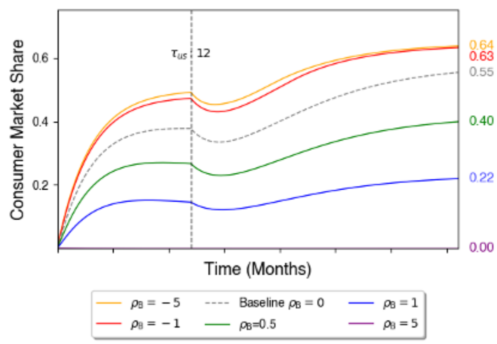
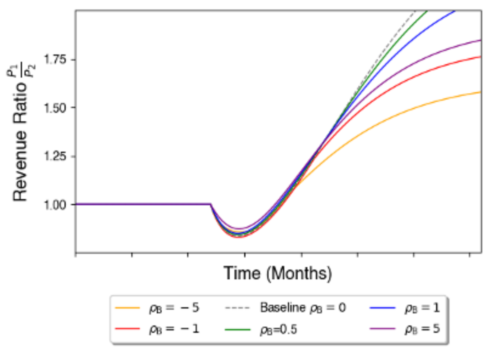
<td>
</td></tr>
<tr><td>We model increasing values of average desired transactions (α), and we focus on the consumer market share for the transparent platform *(MS_{B,P_1})*. Compare outcomes against the benchmark case $\alpha = 1$in dashed gray above</td>
<td>We show the Revenue Ratio ($\frac{Rev_{P1}}{Rev_{P2}}$), 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 3.13 shows the effects of variation in the consumer valuation of their Outside Option below:

<table>
<tr><th colspan="2">Figure 3.13: Effects of Utility of Outside Option for Consumers (ρ_B)</th></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>We model increasing values Utility of the Outside Option for Consumers (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</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 ρ_B</td></tr>
</table>

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.

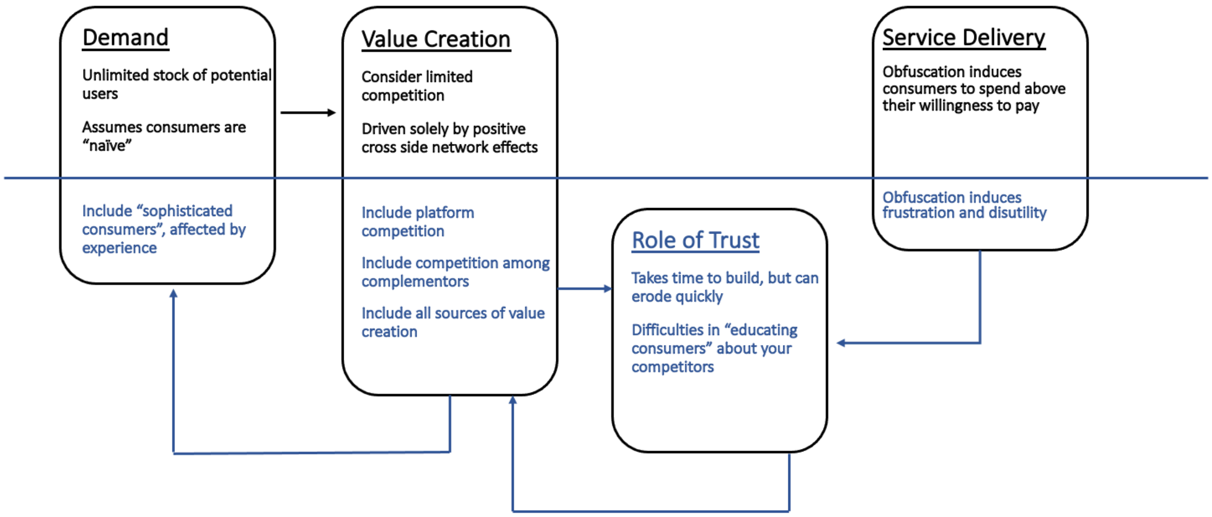
Additional sensitivity analysis is presented in Appendix B.

3.6 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 3.14 below highlights our main contributions. Areas above the blue "water line" have been explored in previous research. In our model, we take into account consumer sophistication (i.e. belief formation about potential future hidden fees based on previous experience); competition between platforms and an outside option; different sources of platform value creation (including same-side competition on the complementor and consumer sides), and an explicit disutility that arises from being shrouded too since, all else equal, consumer prefer a transparent option for the same price (Roman 2010).

Figure 3.14: Contributions.



The use of simulation modeling has allowed to us explore the complex dynamics that arise when multiple platforms compete for multiple complementors and consumers. We have expanded the time horizon to account for the inherent delays in in trust and reputation building.

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. Further work will incorporate Net Present Value calculations, using different Discount Rates to illustrate the inherent financial dynamics.

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. Our work shows that, transparency pays especially when consumers are price sensitive, and have a high penalty on shrouding, but platform firms that move to transparent pricing options need to be cognizant of the time for their consumers to become informed of the drop in hidden fees.

Further work in this stream will build upon this model to account for the role of purchase frequency in updating consumer expectations of hidden fees. The higher the average number of transactions per person per month (α), the faster consumers are likely to learn about changes to the platforms' pricing structure. At low purchase frequencies, it is difficult to have a good prior of what the industry standard is in terms of shrouding or transparency, but it is even harder to have a good prior on what the hidden fee for will be. Likewise, additional future work will explore the roles of word of mouth, and advertising, as potential mechanisms for consumers to become informed of a focal firm's hidden fees, and those of their competitors. One important consideration is that consumers who face hidden fees that are much higher than their original willingness to pay, may drop-off from the purchase process altogether without purchasing, and will be reluctant to return to the platform after, making it harder for them to learn about a potentially more attractive transparent strategy that the platform adopts in the future.

Ongoing work will continue to explore these questions and expand our model to explicitly account for 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 possible 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 instead of the platform (see Figure 3.16.2 in Appendix A). 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 (see Figure 3.17 in Appendix A).

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 3.A

Additional Examples of Price Shrouding in Online Platforms

Figure 3.15: Example of Hidden Fees on Ticket Master. Accessed on November 9th, 2023

Figure 3.15.1

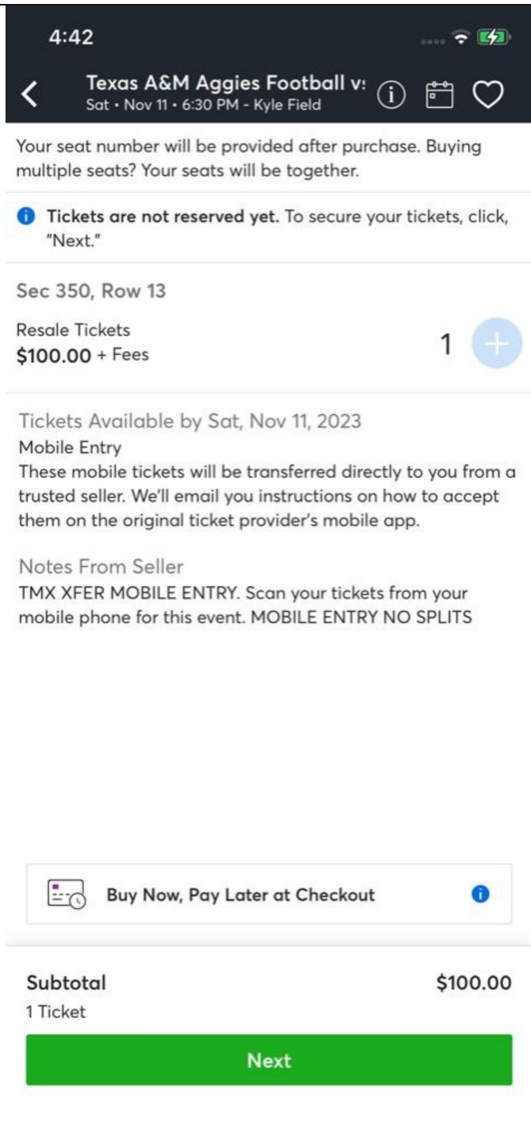
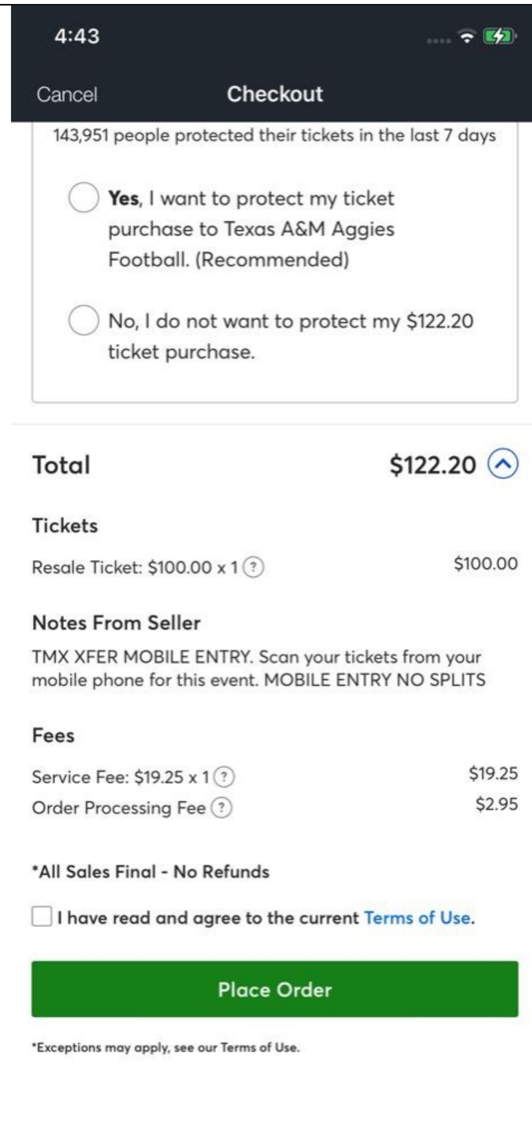


Figure 3.15.2



These screenshots correspond to a typical order for resale tickets on Ticketmaster. Consumers face an initially Visible Price of $100. Compare Table 3.3 against this older version (2023) of the Ticket Master App. The line for "Resale Tickets" has a less salient highlighting of additional fees: smaller font, and gray color. Hovering over the Fees at this stage does not reveal the price.

At the end of the purchase process, additional mandatory Hidden Fees appear. In this example, the Total Price was 22.2% higher than the Visible Price.

Figure 3.16: Example of Hidden Fees on DoorDash. Accessed on May 24th, 2023

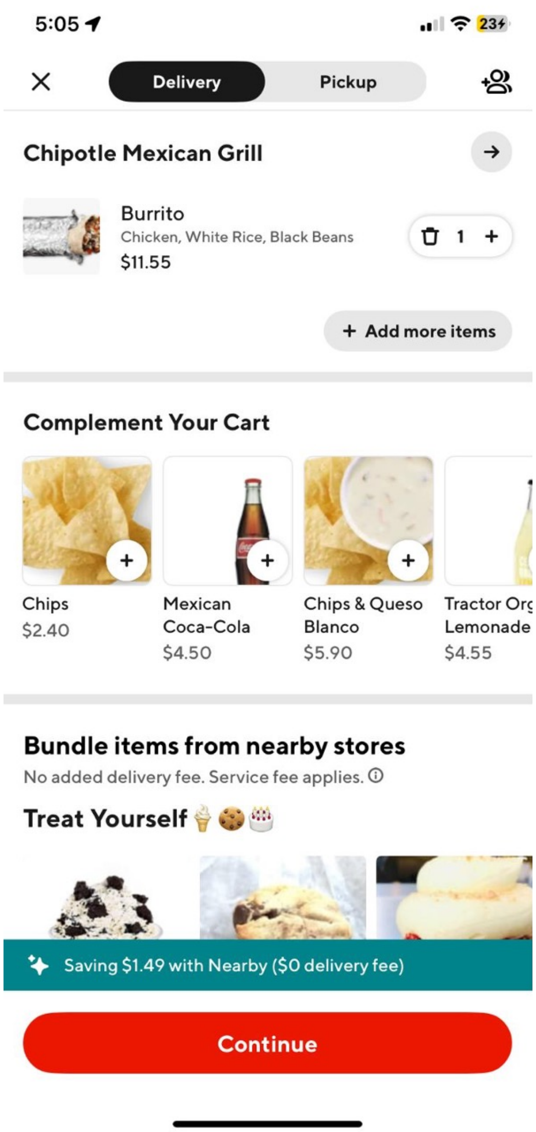
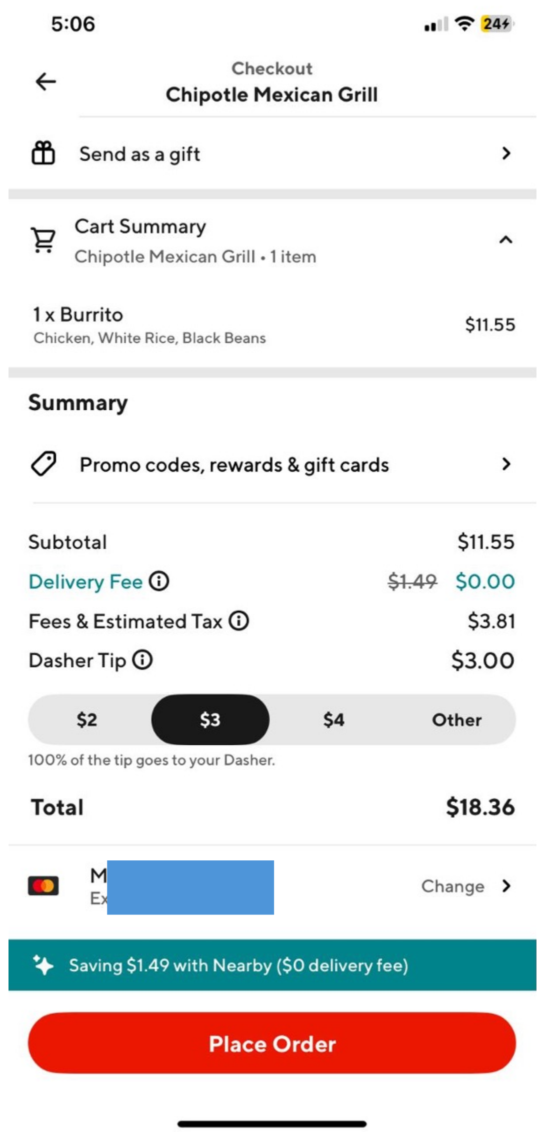
Figure 3.16.1	Figure 3.16.2
	
These screenshots correspond to a typical order for food delivery on DoorDash. Consumers are initially quoted a Visible Price of $11.55. A pop-up at the bottom of the screen shows $0 delivery fee.	Once the consumer has progressed through the different purchase screens, additional fees appear at the end. Not counting Dasher Tips, consumers face mandatory additional charges totaling $3.81. Although the purported $1.49 Delivery Fee discount highlighted in a different color, the remaining Fees' salience is reduced by bundling the with Taxes. By hovering over, previously hidden details break this down into. A $3 Service Fee, and $0.81 estimated tax. The fine print on the Service Fee reads: "This 15.0% service fee (minimum $3) helps us operate Door Dash." In this setting, the Hidden Fee was approximately 26%.

Figure 3.16: Example of Hidden Fees on Airbnb. Accessed on May 2nd, 2024

Figure 3.16.1

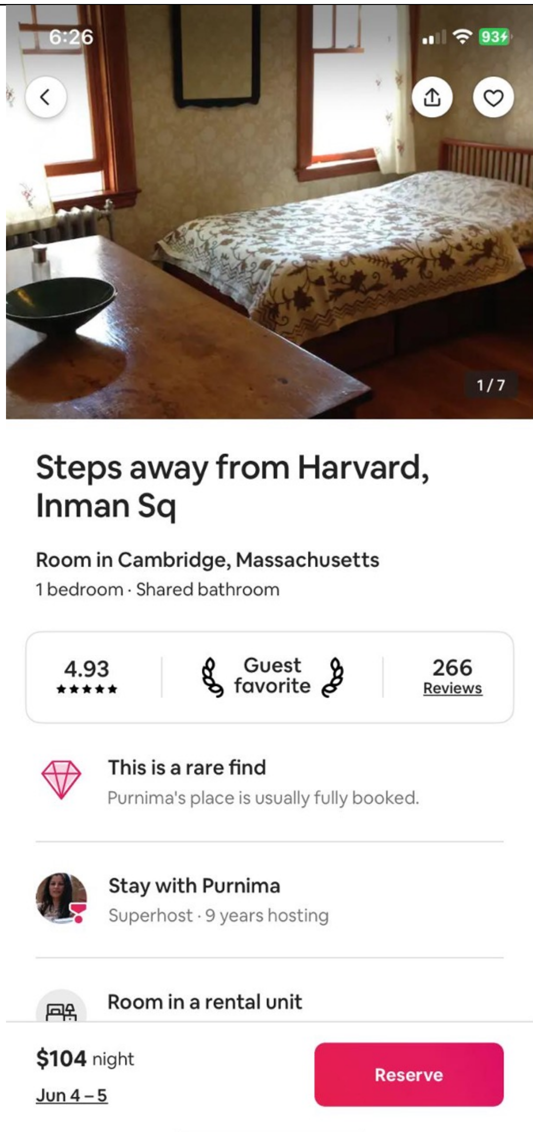
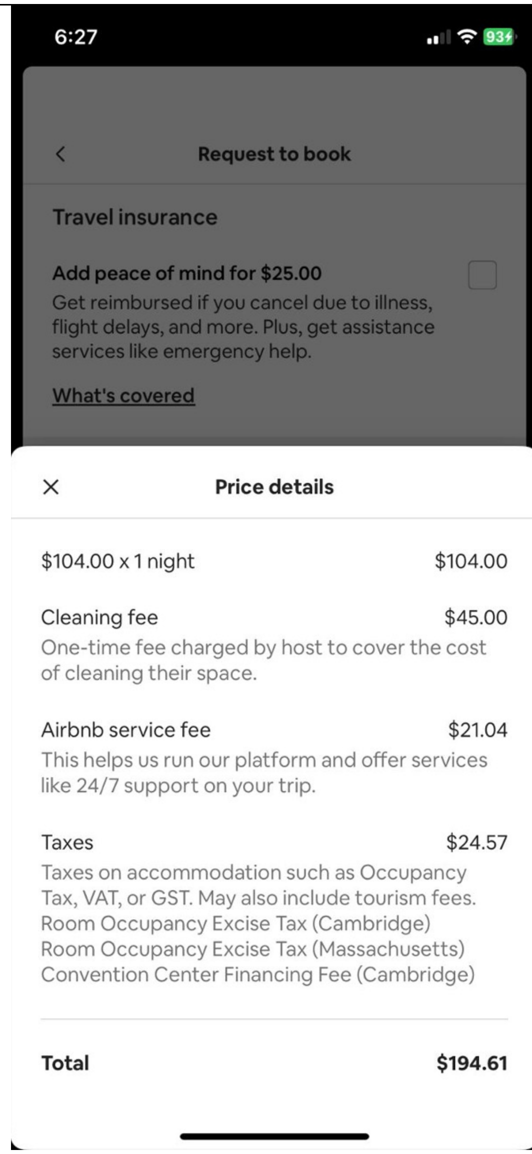


Figure 3.16.2

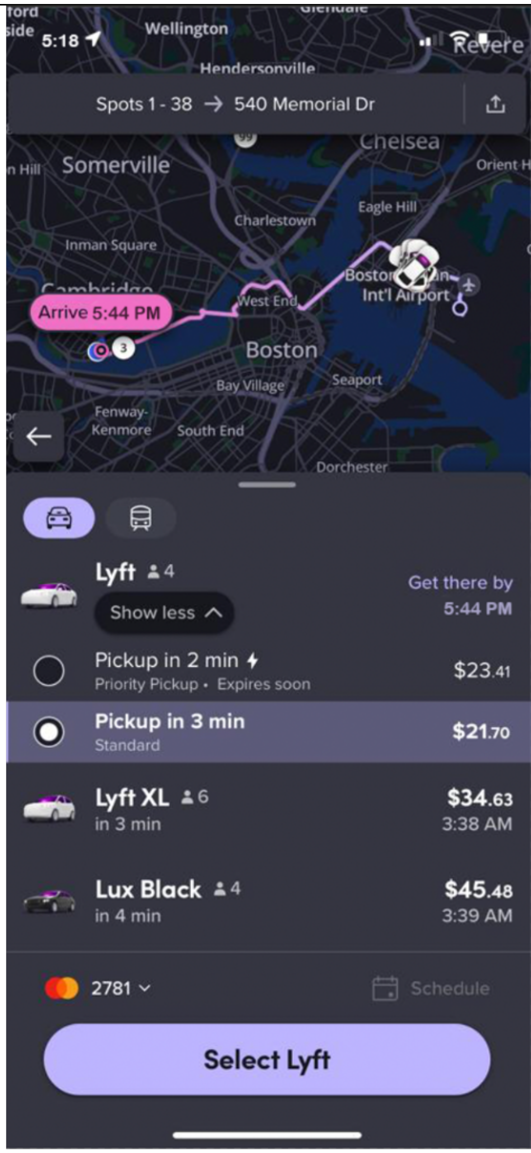


These screenshots correspond to a typical booking for a one-night stay on AirBnb. Consumers are initially quoted a Visible Price of $104. No mention of possible additional fees occurs at this stage.

Once the consumer has progressed through the different purchase screens, additional fees appear at the end. Here, the total price has increased by over 87%. By hovering over, a breakdown is presented that includes 20% service fee. An additional “Cleaning fee” is attributed to the host. There is no mention of whether Airbnb’s service fees’ are calculated as a percentage that includes potential Cleaning fees as well.

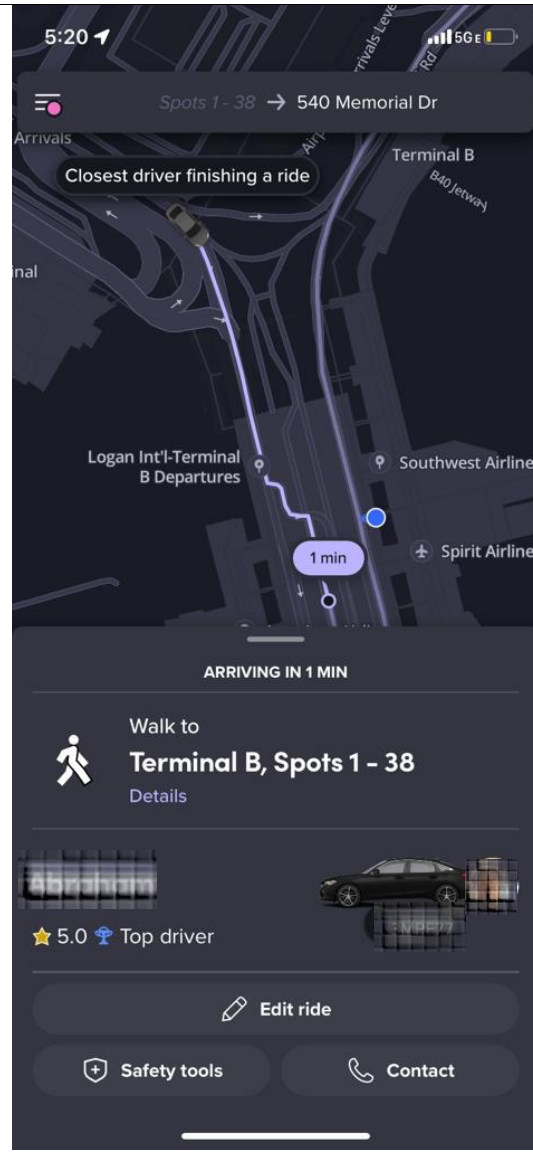
Figure 3.17: Example of Hidden Fees on Airbnb. Accessed on October, 2022

Figure 3.17.1



These screenshots correspond to a ride-hailing purchase on Lyft. Ride hailing platforms can often increase the price when there are demand surges, and will often steer consumers to higher cost options. However, in this setting, we'll focus on Shrouded Wait Times, as an analog to Shrouded Prices. Consumers may anchor on an Initially Visible Wait Time, and decide whether the wait-time to price value proposition is attractive enough to book the service.

Figure 3.17.2



Once the ride has been booked, the ride hailing platforms can update the consumer on their wait time status. If the platform has indication that the wait time will increase, they have at least 2 options on how to disclose this information: On one extreme, they can provide constant updates (every minute). On the other, they can "batch" the updates, and only reveal to the consumer that the wait time has increased, when the driver should have already arrived. This is an example of the second case.

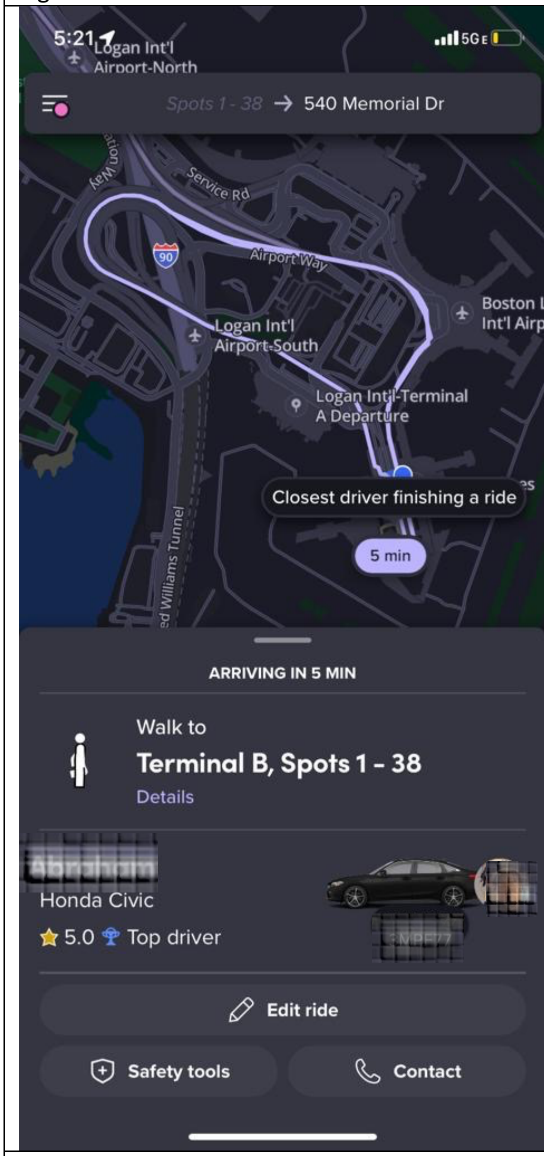
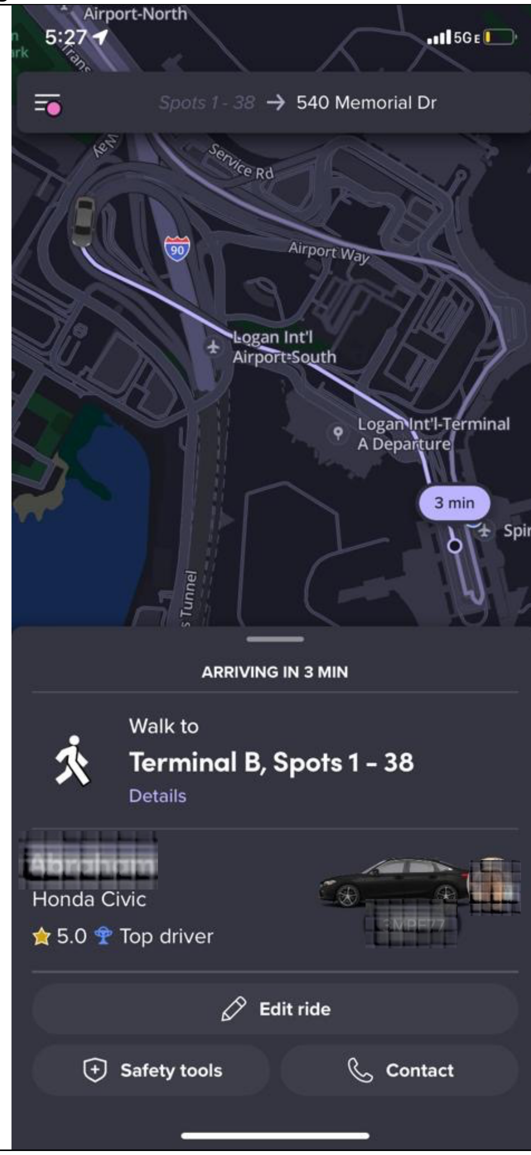
<table>
<tr><td>Figure 3.17.3</td><td>Figure 3.17.4</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>After 3 minutes have elapsed (the Initial Visible Wait Time), the consumer receives an update that the driver is now 5 minutes away.</td><td>After 5 minutes have elapsed (the new “dripped” Wait Time), the consumer receives an update that the driver is still 3 minutes away. Overall, the total wait time for this trim was 12 minutes. An increase in 300% over the Initial Quoted Wait Time.</td></tr>
</table>

Figure 3.17 shows an interesting extension to Shrouded Prices on Ride Hailing Platforms. Even in cases where the ride-hailing platform doesn’t increase the price for consumers, they can increase their attractiveness compared to other platforms or the outside option (in this case a taxi, or some form of public transportation) by quoting short wait times initially and dripping additional wait times as the time progresses. I will explore this idea further in future research.

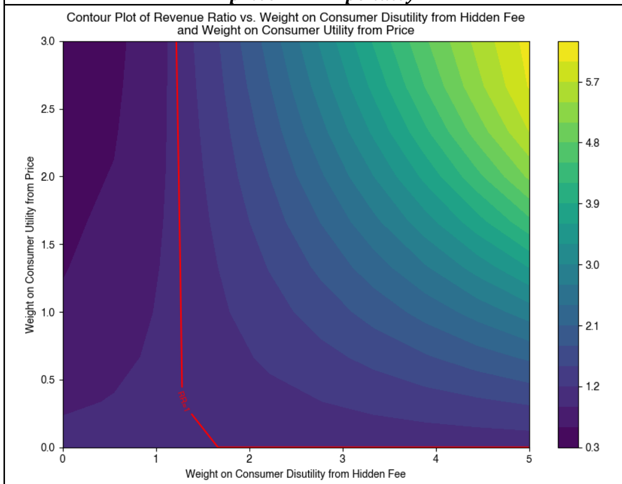
Appendix 3.B

Multivariate Sensitivity Analysis

We briefly explore multivariate sensitivity with the contour plots in Figure 3.18 below. Each varies two parameters from section 3.5 above at the same time and plots the Revenue Ratio ($\frac{Rev_{P1}}{Rev_{P2}}$) as the outcome measure. Revenue Ratios above 1 (shown in increasingly lighter color), show the benefits of transparency for P_1.

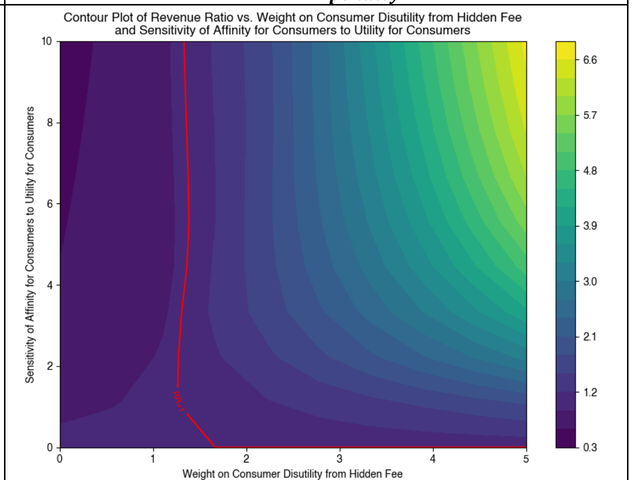
Figure 3.18: Multivariate Sensitivity Analysis

$\boldsymbol{\omega_{price}}$ $\boldsymbol{vs.}$ $\boldsymbol{\omega_{penalty}}$



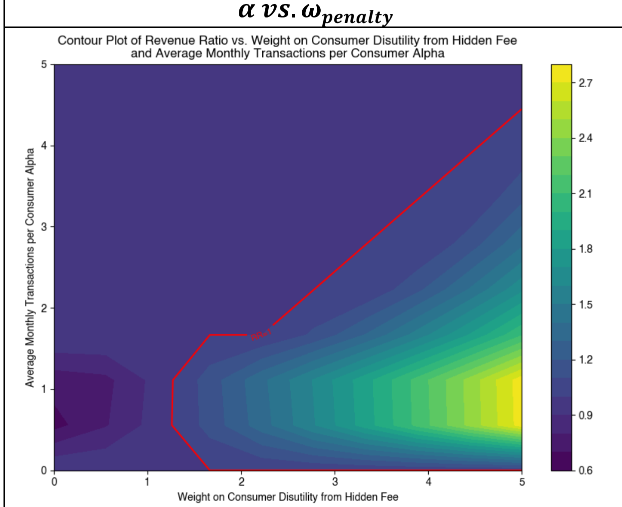
We had previously explored the relationship between price sensistivy and the penalty that consumers place on shrouded hidden fees. For $\boldsymbol{\omega_{penalty}}$ above 1, consumers are more upset at being shrouded to, in line with behavioral assumptions in the literature

$\boldsymbol{\beta_B}$ $\boldsymbol{vs.}$ $\boldsymbol{\omega_{penalty}}$



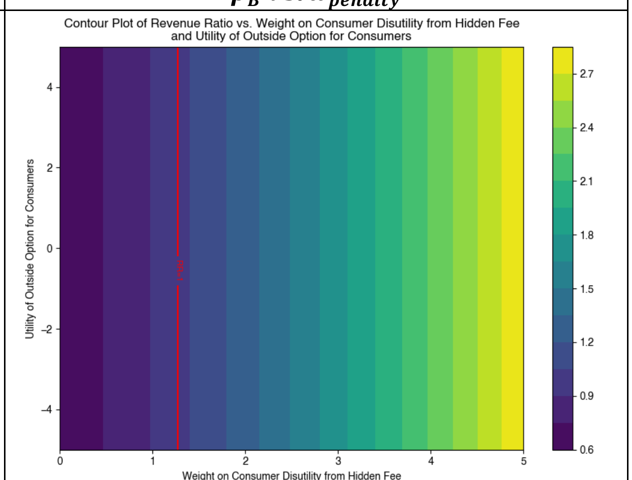
$\boldsymbol{\beta_B}$ is a structural characteristic of the market. In markets with higher $\boldsymbol{\beta_B}$ transparency is more profitable. That is, if consumers are sensitive to differences in utility, the initial drop may be steeper, but more consumers will come back in time.

$\boldsymbol{\alpha}$ $\boldsymbol{vs.}$ $\boldsymbol{\omega_{penalty}}$



At low transaction numbers, the effect of $\boldsymbol{\omega_{penalty}}$ is too small for transparency gains. For value of $\boldsymbol{\alpha}$ much higher than 1, the platforms are no longer able to get consumers to pay ω_{wto} then $\boldsymbol{\omega_{price}}$ puts downward pressure on total prices.*

$\boldsymbol{\rho_B}$ $\boldsymbol{vs.}$ $\boldsymbol{\omega_{penalty}}$

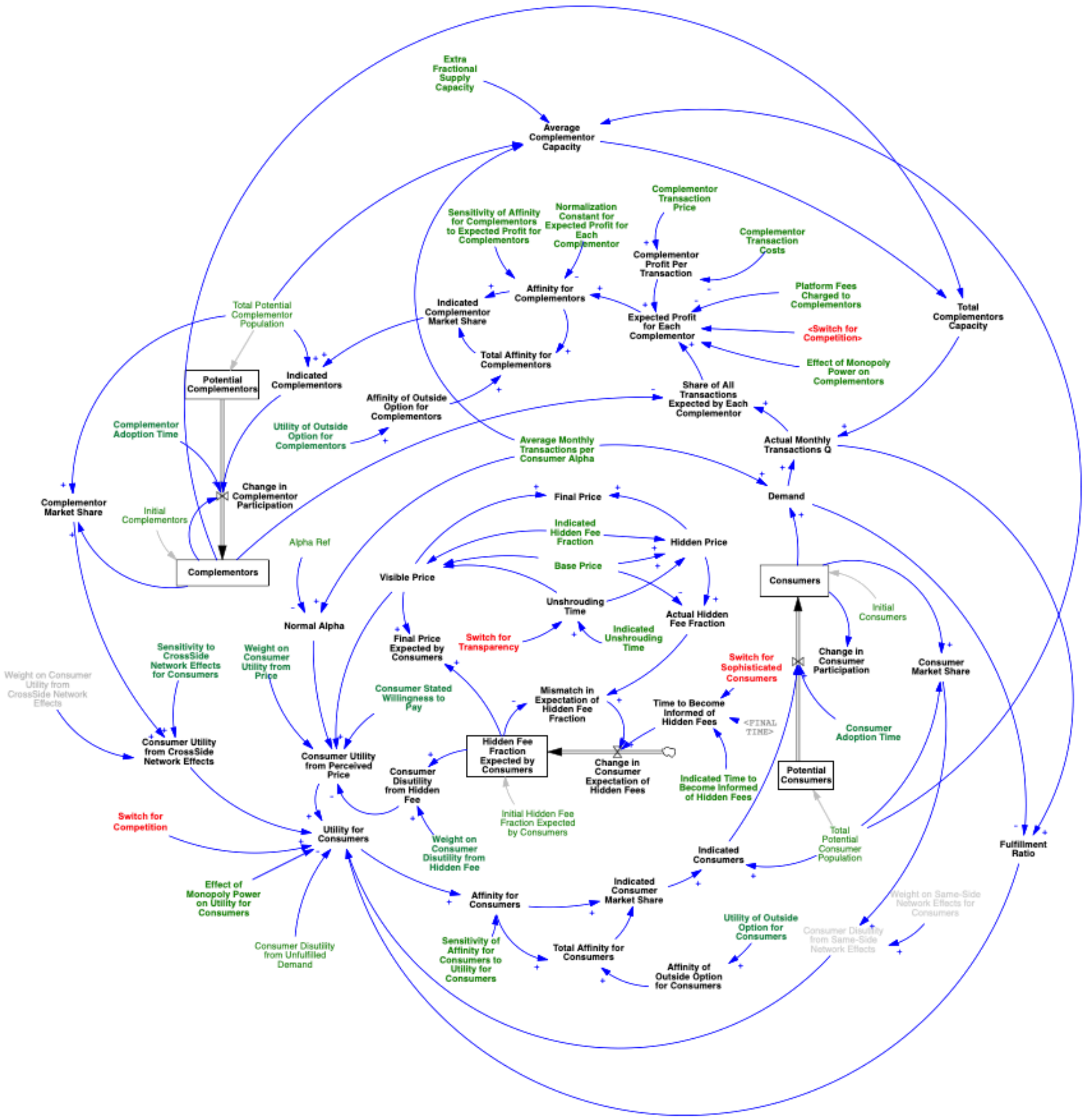


For high values of the outside option, both platforms loose market shares. However, transparency is optimal and it allows P_1 to capture a larger split of the consumers that are potential adopters of either platform.

*Future work explores more sensitivity analysis. As well as the idea that increasing transactions reduces the time to become informed of Hidden Fees.

Appendix C

Vensim Model



Appendix D

Full Model Equations

Actual Hidden Fee Fraction[Platforms]=
Hidden Price[Platforms]/Base Price[Platforms]
Units: Dmnl
The Actual Hidden Fee Fraction is the fraction of the Initial Price that "dripped" to the customers. This is an extra fee added to the Visible Price, as the consumers move through the purchase process. When a platform 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(Sensitivity of Affinity for Complementors to Expected Profit for Complementors
*Utility of Outside Option for Complementors)
Units: Dmnl

Affinity of Outside Option for Consumers=
EXP(Sensitivity of Affinity for Consumers to Utility for Consumers*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 Complementor Capacity is the capacity of each individual
complementor required clear the market if all potential
consumers and complementors joined. Assumes that the
complementors have identical capacity.

Average Monthly Transactions per Consumer Alpha=
1
Units: Transaction/(Month*People) [0,10,0.01]
The Average Monthly Transactions per Consumer (Alpha) is the
average transactions per month that each consumer makes on the
platform they adopt.

Base Price[Platforms]=
1
Units: Dollars/Transaction
The Base Price is a reference price that does not include the
Hidden Price.

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, 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]=
0.6, 0.6
Units: Dollars/Transaction
The Complementor Transaction Price (or Pservice) 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
Units: Dollars/Transaction [1,2,0.1]
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 exponential formulation captures both the effects of variety from additional complementors, and the decreasing marginal utility that each new complementor can provide to each consumer.

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=
-200
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
A measure of how much additional capacity each complementor could fulfill if consumers's demand increased.

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]=
Base 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 Initial Price that "dripped" to the customers. This is an extra fee added to the Visible Price, as the consumers move throught the

purchase process.

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
=
2
Units: Dmnl [0,15,0.1]

Sensitivity of Affinity for Consumers to Utility for Consumers=
2
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
This is the total supply on the platform that can be offered to consumers.

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]=
Base 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.