Analytical Models for Strategic Decisions in Settings with Asymmetric Information

by

Yunke Mai

Business Administration
Duke University

Date: ____________________

Approved:

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Aleksandar Saša Pekeč, Supervisor

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Ali Makhdoumi

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Peng Sun

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Bin Hu

Dissertation submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in Business Administration
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Abstract

This dissertation studies managerial problems involving strategic considerations under asymmetric information. Specifically, we build analytical models to investigate three problems.

The first problem relates to how riders' and drivers' behavior evolves in response to a ride-hailing platform's operational decisions, and study how it impacts the platform's performance and the social welfare. We build an evolutionary game theory model to establish two sustainable asymptotically stable equilibria of the dynamic system of the platform, one resembling a traditional taxi service while the other resembling a successful ride-hailing platform. Using this characterization, we then show how the platform could leverage operational tools at its disposal to optimize its performance. Finally, we establish that a platform can generally improve social welfare and may achieve the socially optimal state by prioritizing high-rating riders in matching under supply shortage. Our analysis highlights the importance for ride-hailing platforms to implement and strategically leverage rider ratings, and can potentially provide guidelines for improving platform performance not just with standard instruments such as price and wage adjustments, but also by making rider rating-driven adjustments into the matching procedure.

The second problem relates to managing innovation spillover risk in sourcing. In particular, when an innovator sources for an innovative product from a supplier who is also a competitor in the end market, the potential innovation spillover may

be a serious concern. Will an innovation ever source from a competitor-supplier in the presence of innovation spillover? We attempt to answer this question with an emphasis on the ex-ante uncertain values of innovations, and distinguish between technical innovations which can only spill over through sourcing and non-technical innovations which can spill over through sourcing as well as in the market. We find that for both types, an innovator may strategically source from a competitor-supplier, albeit for polar-opposite motivations: for technical innovations it does so such that the latter would postpone launching the innovative product; and for non-technical innovations it does so such that the latter would immediately launch the innovative product alongside the innovator. These insights highlight the richness of and may inform sourcing decisions in the presence of innovation spillover.

The third problem relates to information acquisition and technology adoption decisions in a partnership. Using classical information acquisition and technology adoption results for a single decision-maker as a benchmark, we establish that it could be optimal for the partnership to prematurely adopt/reject the technology. Furthermore, anticipating premature decisions in a later period could trigger unraveling which leads to a series of premature decisions in earlier periods. Finally, for a given precision of the partnership's belief of the success probability of the technology, the structure of the optimal policy may be non-monotonic in the belief, due to the non-convexity and discontinuity of the associated coupled optimization problem. Thus, the presence of a partner may have a non-trivial and profound impact on the prescribed optimal information acquisition and technology adoption decisions.

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1

Introduction

This dissertation studies competitive considerations and strategic decisions in complex managerial problems in sharing economy platforms and technology and innovation management. We build analytical models to study three problems. The first problem, which is presented in Chapter 2, studies how user behavior evolves over time on a sharing economy platform by applying and extending concepts from evolutionary game theory, which is often used to model competitions of surviving strategies in a population. The second problem, which is presented in Chapter 3, involves strategic decisions of an innovator and its competitor in the presence of innovation spillover, motivated by interesting real-world co-opetitive supply chain relationships such as the one between Apple and Samsung — Apple sources critical components from Samsung while suing Samsung for patent infringement. The third problem, which is presented in Chapter 4, relates to the optimal technology adoption and information acquisition decisions in a partnership — a novel twist of a classical problem that has been extensively studied in the decision analysis literature.

1.1 Understanding and Shaping User Behavior in Ride-hailing

One of the most heated discussions among drivers on ride-hailing platforms such as Uber and Lyft is their bad experiences when providing services to riders. On the other hand, some riders on the platforms are frustrated about being rejected services by drivers because of low rider ratings. Thus, we want to understand how riders' conduct (which may affect drivers' utilities during service) and drivers' selective behavior (which may lead to rejections of platform-proposed matches and consequently affect riders' privilege to receive timely service and the platform's matching volume) evolve on a ride-hailing platform in the presence of rider ratings (which are used to reflect typical conduct of riders and are provided to drivers), and study how the platform could use operational tools at its disposal to improve not just its performance but also the social welfare.

While drivers and riders are generally not perfectly informed about the state of the platform (e.g., supply or demand shortage), they may shift their behavior (e.g., riders start to improve their ratings, or drivers start to become more selective) based on their own experiences and communications with peers. I find evolutionary game theory to be a perfect tool for modeling the evolution of user behavior in ride-hailing, where the shift in behavior based on their averaged utility is analogous to the shift in surviving strategies in a population based on their averaged fitness.

Utilizing this model, the evolution of user behavior is captured through a dynamic system, more precisely, a coupled ODE system. By analyzing the ODEs, we establish that there are five possible asymptotic states of the system, some of which are asymptotically stable (i.e., the evolution trajectory of user behavior converges to an equilibrium that is robust under random perturbations) while others are not (i.e., the evolution trajectory of user behavior never converges, e.g., it may exhibit oscillating patterns over time). Out of the five possible asymptotic states of the system, we find that only two are asymptotically stable and sustainable for the platform in the sense that drivers and riders would receive positive payoffs and continue to provide/use services on the platform. One such sustainable asymptotically stable equilibrium resembles traditional taxi services while the other resembles successful ride-hailing platforms. In addition, we establish ways how the platform could utilize price and wage adjustments to steer the system towards those two sustainable asymptotically stable equilibria. Interestingly, we show that a platform can generally improve social welfare and may achieve the socially optimal state (which cannot be achieved through only leveraging price and wage adjustments) by prioritizing high-rating riders in matching under supply shortage.

1.2 Managing Innovation Spillover in Sourcing

Apple and Samsung has an interesting relationship: Samsung is the biggest rival of Apple in the smartphone market, yet it is also one of the key suppliers for iPhone components. In fact, such so-called co-opetitive relationship, that a supplier is also a competitor in the same or related market, has become a commonplace as innovators such as Apple mainly focus on their core competences and would thus need to rely on third-party suppliers for value-adding processes. What is interesting is that some of the innovators' proprietary knowledge could become exposed to the competitor-supplier through potential sourcing-related interactions (e.g., Apple had sued Samsung for patent infringement), and yet we are still observing this kind of co-opetitive relationships in industry. So, why would an innovator (such as Apple) source from a competitor-supplier (such as Samsung) in the presence of spillover risk? Could an innovator take advantage of a competitor-supplier's adoption of innovation and actually benefit from innovation spillover? Does timing of a competitor-supplier's adoption of an innovation matter? Do the answers differ for different types of innovations?

In order to address these research questions, we develop an analytical model to study the strategic sourcing decisions for product innovations in the presence of spillover risks. Specifically, we consider an innovator choosing to source between a competitor-supplier and a non-competitor supplier for an innovative product. An essential assumption in the existing literature on knowledge spillover in sourcing is that the transferred knowledge has a known positive value, whereas we focus on managing product innovation spillover with an emphasis on ex-ante uncertain values. Furthermore, we distinguish two types of product innovations, one enhances an existing feature of a product and adds (uncertain) non-negative values to the product while the other introduces a new feature and may either enhance or hurt the value of a product. Interestingly, we find that for both types of innovations, the innovator may strategically source from the competitor-supplier (namely when the latter carries no explicit advantage than the non-competitor supplier). More interestingly, the strategic motivations of sourcing from the competitor-supplier for the two types of innovations are distinct and in fact opposite to each other in terms of the timing of the competitor-supplier's adoption of the innovation. The contrasting insights are driven by subtle yet crucial differences of the two types of innovations, and highlight the richness of and may potentially inform strategic sourcing decisions under innovation spillover risks.

1.3 Technology Adoption and Information Acquisition in a Partnership

There have been extensive decision analysis literature on new technology adoption building upon the classic paper "*Information Acquisition and the Adoption of New Technology*" by McCardle (1985). A critical modeling assumption in this literature is that the considered setting involves either a single decision-maker or a decision-maker and its competitors, which allows for establishing optimal decisions or strategies by solving a single optimization problem or separated optimization problems. However, many business settings require coordination among business partners whose objectives might not be identical. (For example, a high-tech company may need to collaborate with either internal or external partners to jointly advance a new technology innovation.) If the parties involved in the decision-making process are not competitors but are partners instead, what would be the optimal decisions for the partnership?

Motivated by this research question, we develop a dynamic model with a novel twist of the classical single-decision maker setting to capture optimal technology adoption and information acquisition decisions in a partnership. Specifically, we consider two risk-neutral partners, who divide responsibilities for different aspects of decisions for the partnership. Interestingly, we establish that the presence of the partner has non-trivial impacts on the optimal decision policy. In particular, we find that it could be optimal for the partnership to prematurely adopt/reject the technology as compared to the single-decision maker policy, and that the anticipation of premature decisions in a later period could trigger an unraveling effect that leads to a series of premature decisions in earlier periods. These findings establish implications that are not necessarily confined to the context of optimal technology adoption and information acquisition decisions: whenever decision-making responsibilities are assigned to multiple parties with different objectives and consequently leading to decision problems that cannot be decoupled, decisions of one party will likely affect downstream decisions of other parties and could yield to anticipatory decisions and trigger unraveling in the form of a cascading sequence of anticipatory decisions.

2

Understanding and Shaping User Behavior in Ride-hailing

2.1 Introduction

Platform business models are central to the rise, relevance and prevalence of on-demand resource-sharing services. These platforms provide new ways to match supply and demand, create a marketplace, and generate efficient and swift market-clearing transactions. In fact, platform businesses, including ride-hailing services such as Didi Chuxing, Lyft and Uber, and short-term accommodation services such as AirBnB for private parties and WeWork for businesses in need of office space, are among the most valuable "unicorn" companies in the world (CB Insights, 2018).

In this chapter, we focus on ride-hailing platforms, which match drivers and riders on demand in real time. Since drivers and riders need to interact in person and complete services offline after being matched online, they depend on and expect quality matches proposed by the platform. Thus, in order to be successful, a ride-hailing platform needs to ensure quality of service from drivers and appropriate and cooperative conduct from riders. To that end, platforms typically utilize bilateral ratings, i.e., riders and drivers rating each other after service, with an aggregate personal user rating potentially disclosed in future matches proposed by the platform.

Incidentally, ride-hailing platforms use rating information differently for two market sides, and are generally much more stringent towards drivers than towards riders. For example, Uber drivers with ratings of below 4.6/5 or below 4.7/5, depending on the regional market and type of service, are warned that their accounts might be deactivated if their ratings fail to improve (Allen, 2015; Cook, 2015; Rosenblat et al., 2017). As a result, most (and all long-term) Uber drivers have high ratings and, consequently, riders do not need to pay special attention to driver ratings given such heavy-handed regulation imposed by the platform. On the other hand, drivers may discretionarily turn down platform-proposed matches with riders, based on the information provided to them by the platform, including the rider rating. (There is ample anecdotal evidence of such behavior Quora 2017; Reddit 2017. Consequently, riders increasingly pay attention to their rating. Incidentally, Uber recently decided to let riders see their ratings, as reported in Ridester 2018.)

In this chapter we show that a platform could optimize its performance by utilizing rider ratings information when proposing matches to drivers. Specifically, we analyze system performance, including expected payoffs of both riders and drivers and asymptotic states of the system, in a setting in which drivers have an option to be selective , i.e., they can choose to incur cost in order to learn the rating of a rider in a platform-proposed match *before* deciding whether to accept or reject the ride. We establish that the platform can additionally use traditional instruments such as price and wage adjustments, to steer the system towards a sustainable equilibrium state.

The key to our analysis is an inherently asymmetric treatment of riders via their rating which reflects their conduct, and drivers via their selectivity which reflects (not) incurring cost of (not) learning about the rider before accepting/rejecting a platform-proposed match. Specifically, we assume that riders may be either *courteous* or *crude* during service. A courteous rider makes an effort at her own cost to conduct in a way that does not impose any negative externalities on her driver during service. (In this chapter, “courteous” does not refer to specific behavioral patterns, but generally refers to rider behavior which does not negatively affect drivers' utilities.) A crude rider does not make such costly effort and imposes negative externalities on her driver. For example, riders who are not at the correct pick-up location or are late for the start of service waste drivers' time and reduce their earnings. Similarly, riders who are distractive during rides (e.g., loud use of mobile phone, late-night intoxicated home goers) might also impose hardship on the driver. In our model, a rider's conduct is reflected in her rating. (Note that we use the word “crude” as opposed to “rude”, as riders who do not make the effort to behave courteously are likely to be just senseless, i.e., they are crude, and are not necessarily hurting drivers deliberately, i.e., they are not rude.)

On the other hand, we assume that drivers may be either *selective* or *non-selective*, when accepting or rejecting a match proposed by the platform. A selective driver incurs a cost to check rider information (captured by the rider rating in our model) before making acceptance/rejection decision. A non-selective driver does not check rider ratings and accepts all matched riders.

Note that a *social dilemma* arises if a rider's cost of being courteous is less than the damage being crude would impose on her driver: it would thus be socially optimal for a rider to be courteous, but she needs to be incentivized to make such costly effort (in addition to paying the price for the service). This social dilemma plays a central role, and we demonstrate that resolving it (i.e., incentivizing courteous rider behavior at limited driver costs) is pivotal to optimizing platform's performance.

We adopt an evolutionary game theory model in which the behavior of drivers and riders evolves over time in response to their experiences in the platform. On ride-hailing platforms, drivers and riders generally have limited information about the market condition (e.g., local supply or demand shortage). However, over time drivers and riders calibrate the expected payoffs associated with particular behavior, and their collective behavior changes gradually. In our evolutionary model, the proportions of drivers and riders of each behavior describe the state of a dynamic system, and change based on drivers' and riders' expected payoffs in the system. For example, if crude riders receive a higher expected utility than courteous ones, then the proportion of crude riders will increase, and if selective drivers receive a lower utility than non-selective ones, then the proportion of selective drivers will decrease. As such, drivers' and riders' behavior evolves as a dynamic system over continuous time. By analyzing a system of ordinary differential equations describing the dynamic system, we characterize evolutionary trajectories and asymptotically stable equilibria (if they exist), which allow us to understand evolution of user behavior and their welfare, as well as platform performance. We establish that in such a system, there are only two sustainable asymptotically stable equilibria, i.e., equilibria in which the system is stabilized in a state where all drivers and riders have positive expected utilities, and is unaffected by small perturbations.

The first such equilibrium is one where no riders exert efforts to be courteous, while all drivers are non-selective. We show that such an equilibrium emerges when wages are sufficiently high. This equilibrium resembles a traditional taxi service, i.e., the platform's service simply reduces to matching supply and demand. The key for the emergence of this "taxi" equilibrium is that the damage crude riders impose on drivers is relatively small, i.e., negative externality due to lack of rider effort is negligible compared with driver wages.

The second equilibrium is one with non-trivial proportions of both courteous and crude riders and of both selective and non-selective drivers. We show that such an equilibrium emerges when wages (and prices) are sufficiently low. This equilibrium resembles multiple features of a successful ride-hailing platform, i.e., it keeps the price of service attractive by supplementing it with incentivizing courteous behavior from riders, without compromising too much with respect to the number of matched users (as drivers accept crude riders with non-zero probability). In this equilibrium, courteous drivers choose to "pay" for service both monetarily by paying the price platform sets, and non-monetarily by effort to be courteous. The key for the emergence of this equilibrium is that the cost selective drivers incur is low relative to the expected damage from accepting a proposed ride.

We show that this "ride-hailing platform" equilibrium requires that the social dilemma is not negligible: the cost of being a courteous rider is much smaller than the damage imposed to a driver by being a crude rider. A crude rider not getting a ride with some probability is a sufficient incentive for a proportion of riders to be courteous and behave in a socially optimal way (without completely shutting crude riders out of the market). Disclosure of rider ratings to drivers is critical for sustainability of this equilibrium. In summary, this "ride-hailing platform" equilibrium not only provides a matching service, but also unlocks an additional value through facilitating an alternative transfer of utility from courteous riders to drivers.

More generally, our analysis indicates how operational tools can be used to influence the evolution and equilibrium states of the platform users' behavior. We find that, when the system is in a state with a large proportion of crude riders, the platform could incentivize drivers to be more selective (e.g., by lowering wages) to impose pressure on riders to be courteous. On the other hand, when the system is in a state with a large proportion of selective drivers, we find, somewhat surprisingly, that the platform might want to lower the price for riders in order to decrease the number of selective drivers, without necessarily affecting the number of courteous riders.

Note that it is socially optimal for all riders to be courteous as their cost of doing so is lower than the damage crude riders impose on drivers, and for all drivers to be non-selective so as to avoid incurring the cost of being selective. Interestingly, neither of the two sustainable asymptotically stable equilibria (i.e., taxi and ride-hailing platform) are socially optimal as they allow for the existence of (i.e., a non-trivial proportion of) crude riders in equilibrium. However, we show that under supply shortage, a small adjustment in the location-based real-time matching can ensure that the socially optimal state is the unique sustainable asymptotically stable equilibrium. In particular, we establish that a matching policy that locally prioritizes courteous riders under supply shortage (instead of breaking local ties randomly) can sustain this socially optimal equilibrium. Furthermore, we numerically analyze the impact of this adjustment to the matching procedure and show that the total welfare and driver welfare improve significantly, with negligible impact on rider welfare and platform profit.

In the remainder of this section, we briefly discuss related literature. The rest of the chapter is organized as follows. In Section 2.2, we introduce our evolutionary game theory model. In Section 2.3, we identify five possible asymptotic states of the dynamic system and characterize its sustainable asymptotically stable equilibria. We leverage this characterization to identify instruments platform can use to improve its performance, such as wage and price adjustments. In Section 2.4, we analyze an adjustment of the matching scheme that utilizes rider ratings to break local ties, if any, in favor of riders with higher ratings. We provide a sufficient condition for such adjustment to steer the system towards the socially optimal state, and demonstrate numerically that it yields welfare improvements. Section 2.5 provides brief concluding remarks.

2.1.1 Related Literature

Operational issues relevant to managing performance of platforms continue to be one of the most active areas of research in operations management and related areas.

Surge pricing and its impact on ride-hailing platform performance has been the focus of, e.g., Cachon et al. (2017); Castillo et al. (2017); Castro et al. (2018); Chen and Sheldon (2016), and Guda and Subramanian (2018). A variety of pricing questions that are interrelated with other platform design choices such as matching protocol, and are directly related to the supply/demand ratio at both pick-up and drop-off locations, has been widely studied and the following are just a sample of many papers that appeared in the past few years: Banerjee et al. (2016, 2017); Bimpikis et al. (2016); Hu and Zhou (2017b), and Ma et al. (2018). These papers demonstrate a variety of issues that could be managed with pricing, emphasizing the importance of pricing decisions. While we consider pricing as an important operational tool for managing ride-hailing platform's performance, our focus is also on other tools, stemming from leveraging the discrepancy between the cost of riders' efforts to be courteous and the negative externality that crude riders impose on drivers.

A critical real-time optimization problem that ride-hailing platforms need to solve is matching riders and drivers under uncertainty of both supply and demand. These matching issues have been the main focus in several recent papers, e.g., Feng et al. (2017), Gurvich and Ward (2014), Hu and Zhou (2017a), and Ozkan and Ward (2017). To ensure tractability of the equilibrium analysis, we consider an approximate model that matches drivers and riders of nearest neighbors with or without priority, while abstracting away from more algorithmic and computational details.

While driver ratings are important for regulating quality of service, our results show that rider rating information can also be leveraged to improve platform performance and incentivize socially optimal user behavior. The role of ratings in the context of building trust, reputation and signaling quality has been widely studied (Belleflamme and Peitz 2018; Jacobs et al. 2017; Jin et al. 2018; Proserpio et al. 2016; Tadelis 2016; Wang et al. 2017; work in this area produced quite interesting models combining dynamic learning and mechanism design, e.g., Acemoglu et al. 2017; Ifrach et al. 2017) and some of the work focuses on bilateral rating models that are related to the role ratings play in our model, e.g., Belleflamme and Peitz (2018); Jin et al. (2018); Luca (2017), and Tadelis (2016).

There are several recent papers which consider broader operational tools for managing platform performance, e.g., Afèche et al. (2018); Bai et al. (2018); Benjaafar et al. (2018); Feldman et al. (2018); Gurvich and Ward (2014); Hu and Zhou (2017b), and Taylor (2017). (Also, some recent economic papers study impact of informational symmetry and competition, e.g., Jullien and Pavan 2018; Nikzad 2018; Romanyuk 2017.) Our work differs from the aforementioned papers in that we focus on the evolution of user behavior over time and show it has critical impact on the stability and sustainability of ride-hailing platforms.

Kanoria and Saban (2017) is similar in some aspects to our work in the sense that they consider the impact of informational transparency and screening costs in a symmetric or asymmetric two-sided platform setting. Furthermore, Kanoria and Saban (2017) leverage evolutionary game theory to establish stable equilibria, while we track the evolution of user behavior and platform performance as well as provide insights on how to improve system performance by steering it towards a socially desirable equilibrium with our evolutionary game theory model. In our analysis, we utilize classic evolutionary game theory concepts (Easley and Kleinberg, 2010; Sandholm, 2010; Weibull, 1997); we also note that similar replicator dynamics approaches have been used in the context of predicting peer predictions (Shnayder et al., 2016) and in more generic learning contexts (Mostagir, 2010). Finally, the evolutionary game theory approach, with its limits on the information a player has at any given time and consequently limits a player's ability to make well-informed decisions, is related to the concept of mean field equilibria that has been successfully applied in marketplace analytics settings (Adlakha and Johari, 2013; Balseiro et al., 2015; Iyer et al., 2014; Weintraub et al., 2006).

2.2 Evolutionary Game Theory Model

We consider a ride-hailing platform with a continuum of m drivers and a continuum of n riders. (Note that under this continuum formulation of drivers and riders, the supply/demand ratio is m/n.) Riders have a value v for a ride. Platform sets market prices: per-ride price p that a rider pays, as well as per-ride wage w that a driver gets for providing the service. Without loss of generality, we normalize the values of drivers and riders' outside options to be 0. We require $w < p$, which ensures that the platform earns a profit from each matched pair.

Riders could be either *courteous* or *crude*, based on their behavior using the platform's service. Courteous riders make an effort to behave courteously during service and impose no negative externalities to their drivers (e.g., showing up at the correct pick-up location in a timely manner, not being distractive during service, etc.). The effort to be courteous is costly to a rider, and we use parameter $c > 0$ to capture this effort cost. We assume that $v - c > 0$, allowing for courteous riders to have a positive value from the ride. On the other hand, crude riders do not make the effort to behave courteously and incur zero cost, but they impose negative externalities to their drivers (e.g., showing late for the service, being distractive during service, etc.). These negative externalities are captured by the damage to the driver's value from the service, and we use $d > 0$ to denote this damage cost. We assume that at any given time, the platform has sufficient information to reveal rider behavior through rider rating, i.e., courteous riders have high ratings and crude riders have low ratings.

We assume $c < d$, i.e., the cost to a rider of being courteous is less than the damage that the rider would impose on their driver if choosing to be crude. This creates a *social dilemma*: it would be socially optimal for all riders to be courteous, but riders need to be incentivized or compensated for their cost c. In this work, we demonstrate that this social dilemma plays a central role in platform performance. A large $d - c$ (strong social dilemma) suggests a large potential improvement in the platform performance if the social dilemma is resolved. Similarly, if $d - c$ is small (weak social dilemma) there is little potential improvement from resolving the social dilemma. Note that $c < d$ is a natural assumption, for otherwise, it would be socially optimal for riders to be crude and impose damage d to their drivers, i.e., there would be no need to shape user behavior.

To resolve the social dilemma and ensure quality of drivers' experience while providing services, the platform provides rider ratings to drivers and allows drivers to make ride acceptance/rejection decisions at their own discretion and at their own cost. Therefore, drivers could be *selective* or *non-selective*, depending on their preferences to screen riders before accepting/rejecting the ride. Selective drivers check rider ratings and non-selective drivers do not check rider ratings. This screening could be costly to selective drivers (e.g., platform can choose to charge for this information), and we use $f > 0$ to capture the averaged screening cost to drivers per matching period (defined below). On the other hand, non-selective drivers do not incur any screening costs to check rider ratings, and thus accept all matched riders (i.e., both courteous and crude riders). We assume that $w - f > 0$, ensuring that selective drivers could receive a positive payoff from a ride, and $p < v - c$, ensuring that courteous riders could receive a positive payoff from a ride. (Otherwise, the social dilemma surely persists.)

In our model, the platform ensures that every user on the short side of supply and demand will be proposed a match. Specifically, under our continuum formulation of drivers and riders, when there is a supply shortage (i.e., $m < n$), each driver has at least one rider assigned to her for a potential match. Furthermore, given the excess demand (i.e., $n - m$), each driver could have a second rider (e.g., another nearby rider) assigned to her as an additional potential match. Therefore, each driver is assigned either one or two riders as a potential match, with probability $(n-m)/m$ of being assigned two potential matches with (nearby) riders. Similarly, when there is a demand shortage (i.e., $m > n$), each rider is assigned either one or two drivers as a potential match, with probability $(m-n)/n$ of being assigned two potential matches with (nearby) drivers. Note that this implicitly assumes that no market side can be more than twice the size of the other side, i.e., in our matching model we assume that $1/2 < m/n < 2$.

This matching model resembles matching a finite number of drivers and riders according to their proximity in Euclidian space (e.g., a geographic area). If users are positioned uniformly at random, the space can be generically partitioned into disjoint "neighborhoods" so that every neighborhood has one and only one user from the short side of the market (i.e., driver if $m < n$, or rider if $m > n$) and at least one but at most two users from the long side of the market (i.e., riders if $m < n$, or drivers if $m > n$). This partition defines all potential matches: users can be potentially matched if and only if they belong to the same neighborhood. Note that by construction, when $m < n$, the probability of a driver having two potential matches, i.e., having two riders in their neighborhood is exactly $(n - m)/m$. (Similarly, when $m > n$, probability of a rider having two potential matches is $(m - n)/n$.)

Following this resemblance, we define *neighborhood* in our model with continuum of users, to consist of exactly one user from the short side of the market (i.e., driver if $m < n$, or rider if $m > n$) and either one or two users from the long side of the market (i.e., riders if $m < n$, or drivers if $m > n$) assigned as her potential matches. Hence, every neighborhood has at least one and at most two potential matches, and a driver and a rider can be matched only if they are in the same neighborhood (i.e., if they are nearby).

Definition 1 (Nearest-Neighbor Matching)**.** *The nearest-neighbor matching is a platform-proposed matching protocol defined by the following two stages:*

1. First Match (Initial Proposal): Platform proposes one match in every neighborhood. If there are two potential matches in the neighborhood, they have equal chance of being proposed, i.e., the proposed match in the neighborhood is selected at random. Driver of a proposed match decides whether to accept or reject the match.

2. Second Match (Market-clearing): If there are two potential matches in the neighborhood and if the initially proposed match was rejected, the platform proposes the other potential match in the neighborhood. Driver of a newly proposed match decides whether to accept or reject the match.

□

Note that in our model all riders in the system request rides, and only drivers may reject the match proposed by the platform. The nearest-neighbor matching only allows for a possible second chance (but not a third or any subsequent chance) of a user being matched, reflecting the need that drivers and riders be matched as close to instantaneously as possible. With such matching protocol, we assume that after multiple rejections by a driver, the system might already be in a new state and the matching would start anew. Additionally, it may be reasonable to assume that if a rider or a driver needs to wait for a third proposed match, they would leave the system before that (e.g., they could have an alternative option to get or provide service), and thus would not need to be considered in our model. Hence, our assumption that there are at most two potential matches for any user (i.e., $1/2 < m/n < 2$). Further, note that the notion of neighborhood serves a purpose of preprocessing: proposed matches in the nearest-neighbor matching are reduced to preselected potential matches. The platform does not discriminate within a neighborhood (i.e., all users in the neighborhood are nearby) but the matching protocol is simplified by not allowing for matches across neighborhoods. Hence, only nearest neighbors are matched.

We utilize an evolutionary game theory model to study user behavior under the social dilemma and market-clearing set by the platform. Specifically, at any time t, we use parameter s, $0 \leqslant s \leqslant 1$, to denote the proportion of selective drivers, and we use parameter q, $0 \leqslant q \leqslant 1$, to denote the proportion of courteous riders. With this notation, (s, q) denotes the state of the system.

Example 1 ("Taxi" State: $(0, 0)$)**.** *Consider state* $(0, 0)$*, where no drivers are selective and no riders are courteous. In this state, rider rating becomes irrelevant and the platform resembles traditional taxi service. Such "taxi" state is not socially desirable (in the sense that the platform fails to resolve the social dilemma), but it might be feasible and sustainable (in the sense that drivers still receive positive payoffs providing service to riders).* □

Example 2 (Socially Optimal State: $(0, 1)$)**.** *Consider state* $(0, 1)$*, where no drivers are selective and all riders are courteous. In this state, drivers do not incur cost f to check rider ratings, and riders do not impose damage d on drivers during rides. With all riders being courteous and with no drivers checking rider ratings, the social dilemma is resolved at no additional cost, thus the social welfare is maximized.* □

We model evolution of the system state (s, q) over time by the following dynamic system formulation in which the proportion of a behavior that experiences higher (lower) utilities relative to the other behavior gradually increases (decreases) over time. The dynamic system is defined by two ordinary differential equations

$$\frac{ds}{dt} = s(1 - s)(\Pi_D^S - \Pi_D^L), \tag{2.1}$$

and

$$\frac{dq}{dt} = q(1-q)(\Pi_R^A - \Pi_R^B), \tag{2.2}$$

where Π_D^S and Π_D^L are the expected payoffs for selective (S) drivers and non-selective (L) drivers, respectively, and Π_R^A and Π_R^B are the expected payoffs for courteous (A) and crude (B) riders, respectively. We will derive expressions for these expected payoffs in the next section. For now, note that depending on the state of the system (s, q) and values of parameters n, m, p, w, c, d and f, some of these expected payoffs could be negative.

Note that this dynamic system formulation is analogous to the replicator's dynamic in the standard evolutionary game theory literature (e.g., Sandholm, 2010; Weibull, 1997). In our model, the direction and rate of the system's evolution depends on the tradeoffs that riders and drivers face. Riders primarily face the tradeoff between the cost of effort to be courteous versus the risk of being rejected service and consequently receive zero value. Drivers, on the other hand, primarily face the tradeoff between the efforts of being selective versus the damage imposed on them if providing a service to crude riders.

The key assumption of evolutionary game theory approach is that players (i.e., users in our model) may not have full information of the entire system (e.g., drivers may not know the exact total number of riders in the area and vice versa) to make well-informed decisions, but can learn information through repeatedly using the service. Thus, riders and drivers may start with certain behavior and adjust their behavior over time in response to their experiences in the platform. In our evolutionary model, these individual-level changes are captured in aggregate by changes of the distributions of different riders and drivers.

In this evolutionary game theory model, we primarily focus on the solution concept of asymptotically stable equilibrium, which is a refinement of the concept of equilibrium, and is formally defined below. (Note that a state $(\tilde{s}, \tilde{q})$ is defined as an equilibrium of the dynamic system (2.1) and (2.2) if at $(\tilde{s}, \tilde{q})$ the right hand sides of (2.1) and (2.2) are equal to 0.)

Definition 2 (Asymptotically Stable Equilibrium)**.** *An equilibrium $(\tilde{s}, \tilde{q})$ is asymptotically stable if there exists some open neighborhood O of $(\tilde{s}, \tilde{q})$ such that for any $(\hat{s}, \hat{q}) \in O$, state of the system that starts at $(\hat{s}, \hat{q})$ evolves back to $(\tilde{s}, \tilde{q})$.* ▫

Intuitively, an asymptotically stable equilibrium is robust in the sense that a small random perturbation (e.g., a sudden change of conduct of a small fraction of users) that makes the state of the system deviate from the equilibrium point results in users' best responses which steer the state of the system back to the equilibrium point. Mathematically, an asymptotically stable equilibrium is a fixed point that is locally attractive. Moreover, if a fixed point is globally attractive, then it is the unique asymptotically stable equilibrium of the dynamic system.

In our analysis, it is important that all users participate in the platform. They will do so only if their expected payoffs are positive. If either riders' or drivers' payoffs are not positive, they would leave the platform, i.e., the platform would collapse. We capture sustainability of the platform with the following enhancement of the asymptotically stable equilibrium.

Definition 3 (Sustainable Asymptotically Stable (SAS) Equilibrium)**.** *An asymptotically stable equilibrium $(\tilde{s}, \tilde{q})$ is sustainable if drivers and riders' payoffs at $(\tilde{s}, \tilde{q})$ are strictly larger than* 0*.* ▫

Intuitively, a sustainable asymptotically stable (SAS) equilibrium ensures that drivers and riders would not quit the platform, so that the platform does not collapse.

2.3 Equilibrium Analysis

In this section, we conduct equilibrium analysis of the platform performance which is represented by the dynamic system described by differential equations (2.1) and (2.2).

The main result of this section is that there are only two types of candidate sustainable asymptotically stable (SAS) equilibrium states.

Theorem 1. *If* $(\tilde{s}, \tilde{q})$ *is a SAS equilibrium, then either*

(a) $(\tilde{s}, \tilde{q}) = (0, 0)$ *(taxi), or*

(b) $0 < \tilde{s} < 1$ *and* $0 < \tilde{q} < 1$ *(ride-hailing platform).*

Before establishing this result, we first characterize and discuss all possible asymptotic states for the dynamic system.

2.3.1 Characterization of Asymptotic States of the Dynamic System

The characterization is partitioned into six cases, depending on the system parameter values, as illustrated in Figure 2.1. As Figure 2.1 illustrated, the partition is based on two dimensions, supply/demand condition, $n - m$, and the payoff drivers receive from serving a crude rider, $w - d$. Specifically, Cases 1, 2 and 3 correspond to supply shortage, i.e., there are more riders n than drivers m, while Cases 4, 5, and 6 correspond to the platform with excess supply, i.e., there are more drivers m than riders n. The rest of the partition is according to the payoff of a driver serving a crude rider, $w - d$. Cases 3 and 6 correspond to driver's wages being high enough to compensate for damage imposed by serving crude riders, $w - d > 0$, while Cases 1 and 4 correspond to the setting in which the screening cost f is relatively low with respect to drivers' payoff from serving a crude rider, $w - d < -f < 0$. Cases 2 and 5 correspond to the remaining setting of high screening costs, $-f < w - d < 0$. The six cases are formally defined below.

Definition 4. *We denote six blocks of the partition of the parameters as follows.*

Case 1: $n - m > 0$ *and* $w - d < -f$*;*

Case 2: $n - m > 0$ *and* $-f < w - d < 0$*;*

Case 3: $n - m > 0$ *and* $w - d > 0$*;*

Case 4: $n - m < 0$ *and* $w - d < -f$*;*

Case 5: $n - m < 0$ *and* $-f < w - d < 0$*;*

Case 6: $n - m < 0$ *and* $w - d > 0$*.* □

Note that this partition is based on the tradeoffs that drivers face. Specifically, if $n - m > 0$ (i.e., Case 1-3), drivers may get a second match should they reject a crude rider in the first match. If $n - m < 0$, drivers could not get a second match should they reject a crude rider in the first match. On the other hand, if $w - d < 0$ (i.e., Case 1, 2, 4, and 5), drivers want to avoid crude riders, should they check ratings by paying the cost f. If $w - d > 0$ (i.e., Case 3 and 6), drivers have positive payoffs even when they provide service to crude riders.

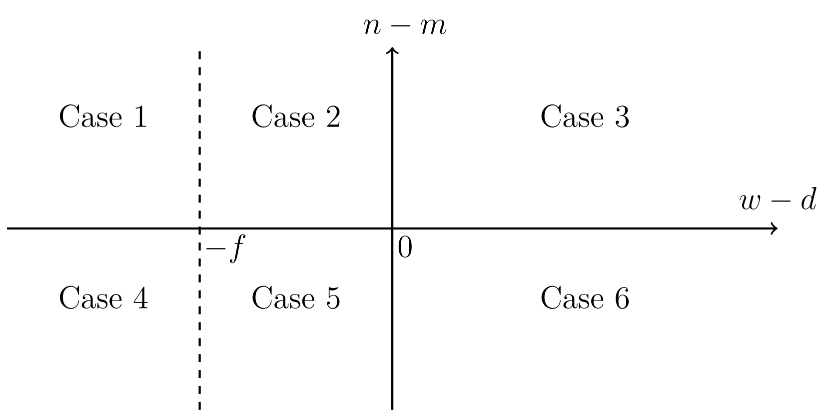

FIGURE 2.1: Six cases for the characterization of asymptotic states

We analyze the dynamic system case by case. First note that the tradeoffs in Cases 5 and 6 are straightforward. Since there is excess supply, drivers would not be able to get a second match should they reject a crude rider. Moreover, since the payoff drivers obtain serving a crude rider is higher than the payoff of screening riders and not serving a crude rider, i.e., $w - d > -f$, it would not be optimal for drivers to be selective in the equilibrium. Since drivers are non-selective, riders have no incentive to be courteous. Thus, we have established the following result.

Proposition 1. *Consider Cases 5 and 6. The unique asymptotically stable equilibrium is* $(0, 0)$.

Proof. Since $w - d > -f$ and $m > n$, no drivers would be selective. Since the system would evolve into a state in which no drivers are selective, no riders would have incentive to behave courteously, i.e., all riders would be crude. Thus, the system would evolve into and stabliizes at $(0, 0)$ in both Case 5 and Case 6 . This completes the proof. □

Next, before characterizing the asymptotic states in Cases 1-4, we provide the expected payoffs for different drivers and riders in these four cases. (These expressions follow directly from probabilities of being matched by nearest-neighbor matching.)

Case 1 and 2: The respective expected payoffs for selective and non-selective drivers are

$$\Pi_D^S = ((1 - \frac{n-m}{m})q + \frac{n-m}{m}(1-(1-q)^2))w - f = qw + (1-q)\frac{n-m}{m}qw - f, \quad (2.3)$$

and

$$\Pi_D^L = qw + (1-q)(w-d). \quad (2.4)$$

The respective expected payoffs for courteous and crude riders are

$$\Pi_R^A = s(1 - \frac{n-m}{m}q\frac{1}{2})(v-p) + (1-s)(1 - \frac{n-m}{m}\frac{1}{2})(v-p) - c, \quad (2.5)$$

and

$$\Pi_R^B = (1-s)(1 - \frac{n-m}{m}\frac{1}{2})(v-p). \quad (2.6)$$

Case 3: The respective expected payoffs for selective and non-selective drivers are

$$\begin{aligned}\Pi_D^S &= (1 - \frac{n-m}{m})qw + \frac{n-m}{m}((1-(1-q)^2)w + (1-q)^2(w-d)) - f \\ &= qw + (1-q)\frac{n-m}{m}(qw + (1-q)(w-d)) - f,\end{aligned} \tag{2.7}$$

and

$$\Pi_D^L = qw + (1-q)(w-d). \tag{2.8}$$

The respective expected payoffs for courteous and crude riders are

$$\Pi_R^A = s(1 - \frac{n-m}{m}q\frac{1}{2})(v-p) + (1-s)(1 - \frac{n-m}{m}\frac{1}{2})(v-p) - c, \tag{2.9}$$

and

$$\Pi_R^B = s\frac{n-m}{m}(1-q)\frac{1}{2}(v-p) + (1-s)(1 - \frac{n-m}{m}\frac{1}{2})(v-p). \tag{2.10}$$

Case 4: The respective expected payoffs for selective and non-selective drivers are

$$\Pi_D^S = q((1 - \frac{m-n}{n}) + \frac{m-n}{n}\frac{1}{2})w - f = q(1 - \frac{m-n}{n}\frac{1}{2})w - f, \tag{2.11}$$

and

$$\Pi_D^L = q(1 - \frac{m-n}{n}\frac{1}{2})w + (1-q)(1 - \frac{m-n}{n}\frac{1}{2}(1-s))(w-d). \tag{2.12}$$

The respective expected payoffs for courteous and crude riders are

$$\Pi_R^A = v - p - c, \tag{2.13}$$

and

$$\Pi_R^B = (1-s)(v-p) + s\frac{m-n}{n}(1-s)(v-p). \tag{2.14}$$

Using these expressions for expected payoffs, we now characterize the asymptotic states in Cases 1-4.

Lemma 1. *Consider Case 1. There exists constant* K_1 *such that*

i) if $\frac{2m(v-p-c)}{(n-m)(v-p)} \leqslant K_1$*, the unique asymptotically stable equilibrium is the boundary point* $(1, \bar{q})$*,* $0 < \bar{q} < 1$*;*

ii) if $\frac{2m(v-p-c)}{(n-m)(v-p)} > K_1$*, the unique asymptotically stable equilibrium is the interior state* (s^*, q^*)*,* $0 < s^* < 1$*,* $0 < q^* < 1$*.*

Proof. In case 1, the dynamic system can be written as

$$\frac{ds}{dt} = s(1-s)G_1(q),$$

$$\frac{dq}{dt} = q(1-q)G_2(s,q),$$

where

$$G_1(q) = \frac{(-1+a)w}{a}q^2 + \left(\frac{w}{a} - d\right)q + (d - f - w),$$

$$G_2(s,q) = s\left(1 - \frac{(1-a)q}{2a}\right)\mu - c.$$

Here, we have arranged

$$a = \frac{m}{n}, \qquad \mu = v - p;$$

hence the relations among the parameters are

$$\frac{1}{2} < a < 1, \qquad d > c > 0, \qquad f < w < d - f, \qquad c < \mu < v - w.$$

Using these conditions, it is immediate that

$$G_1(1) = -f < 0, \qquad G_1(0) = d - f - w > 0.$$

It follows that there exists a unique root of G_1 which belongs to $[0,1]$, and we denote it as q^*, namely,

$$q^* = \frac{(ad - w) - ((w - ad)^2 - 4a(d - f - w)(-1+a)w)^{1/2}}{2(-1+a)w}.$$

Note that $q = q^*$ is a q-nullcline.

The expression $G_2(s, q)$ can be rewritten as

$$G_2(s, q) = \frac{\mu}{2a}(aq + 2a - q)(s - \tau(q)),$$

where

$$\tau(q) = \frac{2ca}{((-1 + a)q + 2a)\mu}.$$

This is always valid since $aq + 2a - q > aq + 1 - q > 0$, by the assumption that $a > \frac{1}{2}$. For all q values of interest, the funciton $\tau(q)$ is a branch of a hyperbola, positive and increasing. Whether or not this branch of hyperbola should intersect the straight line $q = q^*$ depends on the value $\bar{q}$ which satisfies $\tau(\bar{q}) = 1$, that is,

$$\bar{q} = \frac{2a}{1 - a}\frac{\mu - c}{\mu}.$$

In particular, note that $\bar{q} > 0$ always holds, by the assumption on the parameters, however, $\bar{q}$ may be greater than 1.

Let the right hand sides of the original differential equations be denoted as F_1, F_2, respectively. If an interior equilibrium (s^*, q^*) exists, it is easy to verify that

$$\frac{\partial F_1}{\partial s}(s^*, q^*) = 0, \qquad \frac{\partial F_1}{\partial q}(s^*, q^*) < 0, \qquad \frac{\partial F_2}{\partial s}(s^*, q^*) > 0, \qquad \frac{\partial F_2}{\partial q}(s^*, q^*) < 0.$$

Therefore the Jacobian of the system at (s^*, q^*) has negative trace and positive determinant; hence (s^*, q^*) is asymptotically stable. Follow similar argument, we can establish the asymptotic stability for $(1, \bar{q})$.

The stability on the boundaries are easily seen. For instance, the directions on the upper boundary follows from the fact that $G_1(1) < 0$; that on the lower boundary follows from the fact that $G_1(0) > 0$; that on the left boundary follows from $-\tau(0) < 0$; that on the right boundary is distinguished by whether $q > \bar{q}$, following from whether $1 - \tau(q) > 0$.

Let $K_1 = q^*$. This completes the proof. $\square$

Lemma 2. *Consider Case 2. There exist constants Δ_1, K_2, and K_3, $K_3 > K_2$, such that*

i) if $\Delta_1 < 0$ or $m/n > w/d$, the unique asymptotically stable equilibrium is $(0,0)$;

ii) if $\Delta_1 \geqslant 0$ and $m/n \leqslant w/d$, then

a. if $\frac{2m(v-p-c)}{(n-m)(v-p)} \leqslant K_2$, the unique asymptotically stable equilibrium is $(0,0)$,

b. if $K_2 < \frac{2m(v-p-c)}{(n-m)(v-p)} \leqslant K_3$, then there exist two asymptotically stable equilibria: $(0,0)$ and $(1,\bar{q})$, $0 < \bar{q} < 1$,

c. if $\frac{2m(v-p-c)}{(n-m)(v-p)} > K_3$, then there exist two asymptotically stable equilibria $(0,0)$ and (s^*, q^*), $0 < s^* < 1$, $0 < q^* < 1$.

Proof. In this case, the dynamic system is written as

$$\frac{ds}{dt} = s(1-s)G_1(q),$$

$$\frac{dq}{dt} = q(1-q)G_2(s,q),$$

where

$$G_1(q) = \frac{1}{a}\left((-1+a)wq^2 + (w-ad)q + (d-f-w)a\right),$$

$$G_2(s,q) = \frac{(aq+2a-q)\mu}{2a}(s-\tau(q)),$$

and

$$\tau(q) = \frac{2ca}{((-1+a)q+2a)\mu}.$$

Here, we have arranged

$$a = \frac{m}{n}, \qquad \mu = v - p;$$

hence, the parameters satisfy

$$\frac{1}{2} < a < 1, \qquad d > c > 0, \qquad f < w < d, \qquad d - f - w < 0, \qquad c < \mu < v - w.$$

In particular, we have that $G_1(q)$ is a quadratic polynomial in q with negative leading coefficient and

$$G_1(0) = d - f - w < 0, \qquad G_1(1) = -f < 0.$$

Therefore, there may be three possibilities: (i) $G_1(q)$ has no real roots; (ii) $G_1(q)$ has exactly one real root; (iii) $G_1(q)$ has two distinct real roots. Moreover, only in the latter two cases, and only when the roots there in are positive can it be possible for any interior equilibrium of the system to exist.

For now, we will be interested in the cases that are *generic*, namely, when the discriminant $\Delta(G_1) \neq 0$. The expression of G_1 tells us that, once G_1 has two real roots, then they are either both positive or both negative. Consequently, we shall be interested in only two general cases:

- Case I: $\Delta(G_1) < 0$ or $w - ad < 0$;
- Case II: $\Delta(G_1) > 0$ and $w - ad > 0$.

To put in familiar terms, the first case is precisely when $G_1 = 0$ gives rise to no valid s-nullclines; the second case is when $G_1 = 0$ gives rise to two distinct s-nullclines. (Because $G_1(0) > G_1(1)$, we know that the two positive roots of G_1, once exist, must be in between $(0, 1)$.)

On the other hand, a q-value is of importance, namely, the one such that

$$\tau(q) = 1.$$

As before, we denote it as $\bar{q}$ and it has the value

$$\bar{q} = \frac{2a}{1-a} \frac{\mu - c}{\mu}.$$

In particular, note that $\bar{q}$ is always positive.

The following results would follow.

Case I

In Case I, the only equilibrium that is asymptotically stable is $(s, q) = (0, 0)$. The only equilibrium that can exist other than the four corners of $[0, 1] \times [0, 1]$ is $(1, \bar{q})$, which occurs precisely when $\bar{q} < 1$.

Case II

In this case, let q_1^*, q_2^* $(0 < q_1^* < q_2^* < 1)$ denote the two distinct positive roots of $G_1(q)$. Based on the possible values of $\bar{q}$, we have the following four cases.

In Case II, if $\bar{q} \geqslant 1$, the equilibria of the system are the four corners of $[0, 1] \times [0, 1]$, together with two additional points $(\tau(q_1^*), q_1^*)$ and $(\tau(q_2^*), q_2^*)$. Among these equilibria, $(0, 0)$ and $(\tau(q_2^*), q_2^*)$ are asymptotically stable, the other equilibria are unstable.

To see why this is the case, note that the Jacobi matrices at $(\tau(q_1^*), q_1^*)$ and $(\tau(q_2^*), q_2^*)$ have, respectively, signature:

$$\begin{pmatrix} 0 & + \\ + & - \end{pmatrix}, \qquad \begin{pmatrix} 0 & - \\ + & - \end{pmatrix}.$$

The stability of $(\tau(q_i^*), q_i^*)$ $(i = 1, 2)$ then follows. The stability of $(0, 0)$ is evident by a slope field plot. In Case II, if $q_2^* < \bar{q} < 1$, the equilibria of the system are the four corners of $[0, 1] \times [0, 1]$, together with three additional points $(\tau(q_1^*), q_1^*)$ and $(\tau(q_2^*), q_2^*)$ and $(1, \bar{q})$. Among these equilibria, $(0, 0)$ and $(\tau(q_2^*), q_2^*)$ are asymptotically stable, the other equilibria are unstable. The stability of $(\tau(q_i^*), q_i^*)$ $(i = 1, 2)$ follows from an argument identical to the previous proposition. The stability of $(0, 0)$ and $(1, \bar{q})$ is evident by a slope field plot.

In Case II, if $q_1^* < \bar{q} \leqslant q_2^*$, the equilibria of the system are the four corners of $[0,1] \times [0,1]$, together with two additional points $(\tau(q_1^*), q_1^*)$ and $(1, \bar{q})$. Among these equilibria, $(0,0)$ and $(1,\bar{q})$ are asymptotically stable, the other equilibria are unstable.

The stability of $(\tau(q_1^*), q_1^*)$ follows from an argument identical to the previous proposition. In Case II, if $0 < \bar{q} \leqslant q_1^*$, the equilibria of the system are the four corners of $[0,1] \times [0,1]$, together with the additional point $(1,\bar{q})$. Among these equilibria, only $(0,0)$ is asymptotically stable, the others are unstable. The stability of $(0,0)$ and $(1,\bar{q})$ is evident by a slope field plot.

Let $K_2 = q_1^*$ and $K_3 = q_2^*$. This completes the proof. □

Lemma 3. *Consider Case 3. The unique asymptotically stable equilibrium is* $(0,0)$. *There exist constants* Δ_2 *and* K_4 *such that, if* $\Delta_2 > 0$ *or* $K_4 < 1$, *and if* $\frac{2mc}{(3m-n)(v-p)} < 1$, *there exists one other stationary equilibrium* (s^*, q^*), $0 < s^* < 1$, $0 < q^* < 1$, *which is not asymptotically stable and the evolution trajectories of* (s,q) *that are sufficiently close to* (s^*, q^*) *exhibit constant periodic patterns.*

Lemma 4. *Consider Case 4. The unique asymptotically stable equilibrium candidate is* $(0,0)$.

i) If $\frac{(3-m/n)(w-d)-2f}{(m/n-1)(w-d)} < 0$, *there exists no asymptotically stable equilibrium, and the evolution trajectory of* (s,q) *diverges and exhibits periodic patterns over time.*

ii) $\frac{(3-m/n)(w-d)-2f}{(m/n-1)(w-d)} \geqslant 0$, $(0,0)$ *is the unique asymptotically stable equilibrium.*

Proof. The proofs of Lemma 3 and 4 follow similar analyses as in the proof of Lemma 1 and 2. □

The proofs require establishing equilibria and conducting stability analysis for the system of ordinary differential equations (2.1) and (2.2) with appropriate payoff expressions, depending on the case considered.

We next discuss in detail properties of the five possible asymptotic states of the dynamic system which were identified in the previous subsection.

Divergence (unstable): This divergence state emerges in Case 4 based on the characterization in Lemma 4.

The system converges to an unstable state in which the trajectories of (s, q) diverge in circles (as illustrated in Figure 2.2), i.e., the proportions of courteous riders and selective drivers oscillate over time and the degree of oscillation becomes stronger and stronger. Such divergence state of the system is unsustainable as it is unstable and the trajectories of (s, q) would pass through phases in which driver welfare is negative, i.e., drivers would quit the platform and the platform collapses.

Example 3. *Consider a setting with demand shortage,* $m/n = 6/5$ *and normalize the value of a ride to riders at* $v = 1$*. Let the price of the service be set at* $p = 0.7$*, wage for drivers set at* $w = 0.5$*, and driver's screening cost set at* $f = 0.2$*. Further set the damage that crude riders impose on their drivers at* $d = 0.8$*, and cost to riders to be courteous at* $c = 0.15$*. It follows from Lemma 4 that the asymptotic state of the dynamic system is divergence. The evolution trajectory of driver welfare (based on the evolution trajectory of* (s, q)*) is depicted in Figure 2.3. The plot suggests that the trajectory of driver welfare oscillates over time and passes through phases where driver welfare is below* 0 *(which correspond to states where* s *is high, i.e., the proportion of selective drivers is high, and* q *is low, i.e., the proportion of courteous riders is low).*

□

Note that what we illustrate through Example 3 holds for every divergence state, i.e., for every divergence state driver welfare would pass through phases in which it becomes negative, as the evolutionary trajectory diverges towards the corner close to $(1, 0)$ (where all drivers are selective yet no riders are courteous).

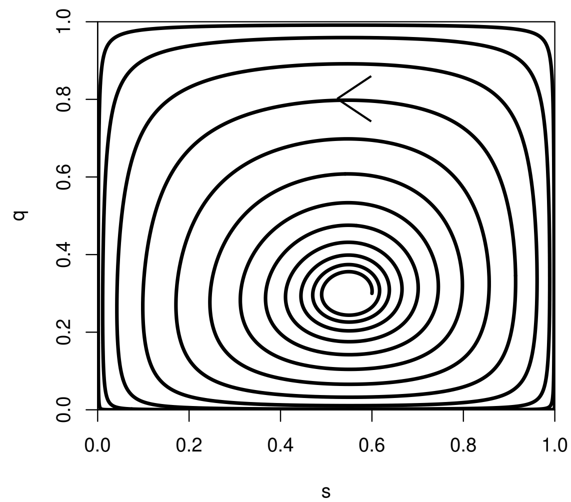

FIGURE 2.2: Divergence state

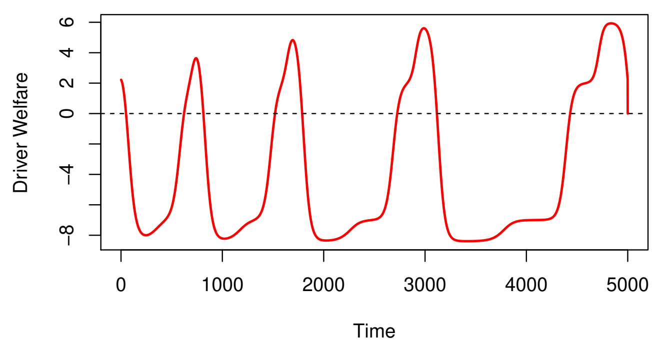

FIGURE 2.3: Driver welfare under divergence state

Cyclical (unstable): This cyclical state emerges in Case 3 based on the characterization in Lemma 3.

The system converges to an unstable state in which the trajectories of (s, q) draw constant circles (as illustrated in Figure 2.4), i.e., the proportions of courteous riders and selective drivers oscillate over time and the degree of oscillation is constant. Such cyclical state is also unsustainable as either the evolutionary trajectories of (s, q) would pass through phases where driver welfare becomes negative (similar to the divergence state as we just discussed), or a random perturbation would push the evolutionary trajectories out of the cycling orbit and the system would converge to a different asymptotic state that coexists with cyclical (as we will discuss later).

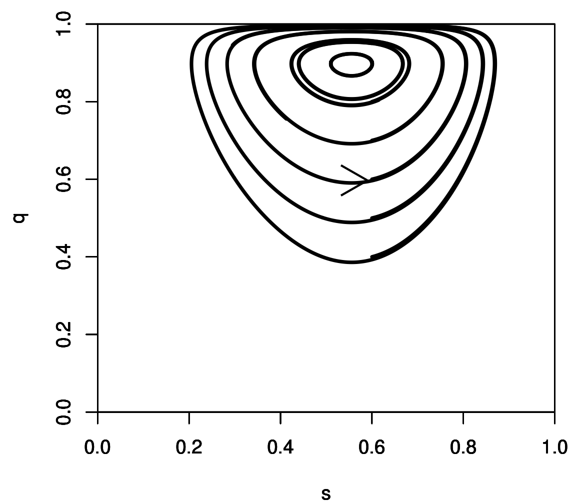

FIGURE 2.4: Cyclical state

Note that the trajectories in the divergence and cyclical states are counter-clockwise: at the lowest point of the trajectories where q, the proportion of courteous riders, is low, drivers start to become more selective, i.e., s starts to increase. As the proportion of selective drivers increases, riders are incentivized to become more courteous, i.e., q starts to increase. As the proportion of courteous riders increases to some point, drivers start to become less selective, i.e., s starts to decrease. As the proportion of selective drivers decreases to some point, riders start to become less courteous, i.e., q starts to decrease.

"Taxi" (asymptotically stable equilibrium $(0, 0)$): This "taxi" state could emerge in all cases except Case 1 based on the characterization in Proposition 1, Lemma 2, 3, and 4.

The system converges to an asymptotically stable equilibrium in which no drivers are selective and no riders are courteous (as illustrated in Figure 2.5). This equilibrium resembles a traditional taxi service, i.e., the platform's service simply reduces to matching supply and demand. In this "taxi" state, the social dilemma remains unresolved as the cost of being selective for drivers is too high, and without drivers' selective behavior riders have no incentive to behave courteously. However, $(0, 0)$ may be sustainable for the platform in the sense that drivers' and riders' payoffs are strictly positive, when the platform sets high enough wage w so that rides are profitable for (non-selective) drivers, i.e., $w - d > 0$.

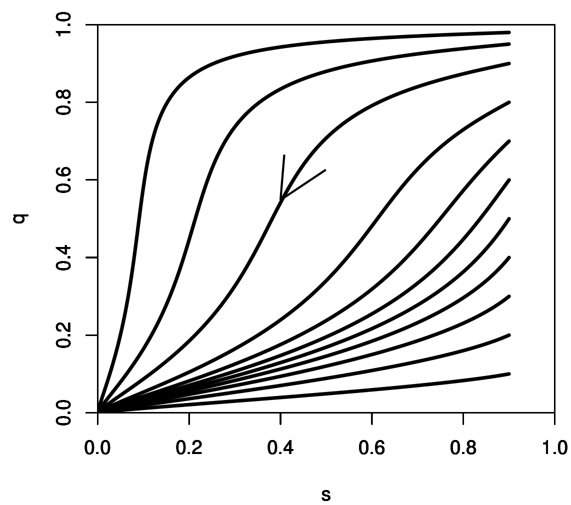

FIGURE 2.5: "Taxi" state $(0, 0)$

"Ride-hailing platform" (asymptotically stable equilibrium (s^*, q^*)): This "ride-hailing platform" state could emerge in Case 1 or 2 based on the characterization in Lemma 1 and 2.

The system converges to an asymptotically stable equilibrium in which there is a mix of selective and non-selective drivers, and a mix of courteous and crude riders (as illustrated in Figure 2.6). This equilibrium resembles a successful ride-hailing platform, i.e., it incentivizes courteous behavior from riders, without compromising too much with respect to the number of matched users (as drivers accept crude riders with non-zero probability). In this equilibrium, courteous riders choose to "pay" for service both monetarily by paying the price platform sets, and non-monetarily by effort to be courteous. Consequently, with the appropriate wage w and price p, the system enters a sustainable state in which all participants continue using the platform and obtain positive payoffs from either providing or using the service.

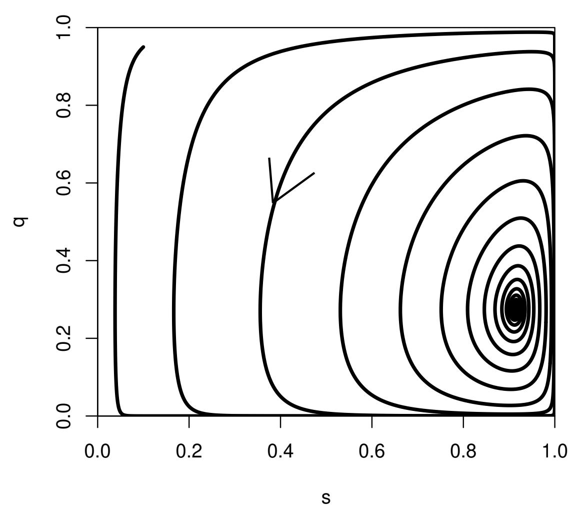

FIGURE 2.6: "Ride-hailing platform" state (s^*, q^*)

Over-selective (asymptotically stable equilibrium $(1, \bar{q})$): This over-selective state could emerge in Case 1 or 2 based on the characterization in Lemma 1 and 2.

The system converges to an asymptotically stable equilibrium in which all drivers are selective but not all riders are courteous (as illustrated in Figure 2.7). This equilibrium is non-sustainable, as $1 - \bar{q}$ of riders (crude riders) quit the platform as all drivers are selective and thus reject any matches with crude riders. Hence, crude riders are never serviced and leave the platform which may eventfully lead to platform collapse.

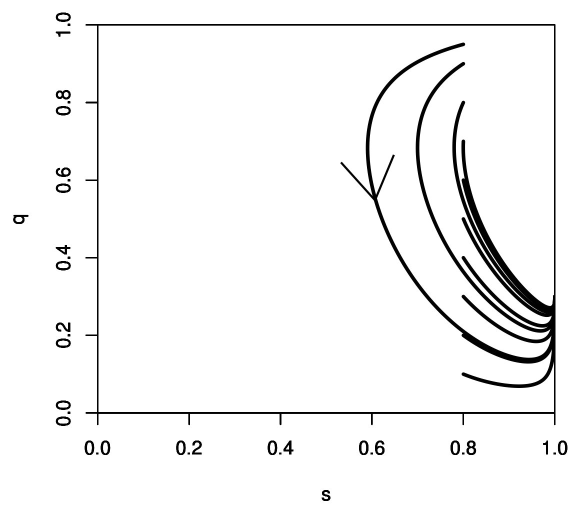

FIGURE 2.7: Over-selective state $(1, \bar{q})$

2.3.2 Sustainable Asymptotically Stable Equilibria

Now after we characterized and discussed all asymptotic states of the system, we are ready to establish Theorem 1. Figure 2.8 summarizes all possible asymptotic states by cases. Case 2, 4, and 5 are not sustainable from the platform's perspective as they do not contain any SAS equilibrium (which are marked in blue in Figure 2.8). In particular, Case 5 is unsustainable as the (unique) asymptotic state of the system is $(0, 0)$ and drivers would quit the platform as $w - d < 0$. Case 4 is unsustainable as the asymptotic state of the system is either $(0, 0)$ (and drivers would quit the platform since $w - d < -f < 0$), or unstable divergence (and drivers would also quit the platform as previously discussed). Case 2 is unsustainable as $(0, 0)$ is always an asymptotically stable equilibrium (drivers would quit the platform as $w - d < 0$) even though stable equilibria other than $(0, 0)$ are also possible, depending on the

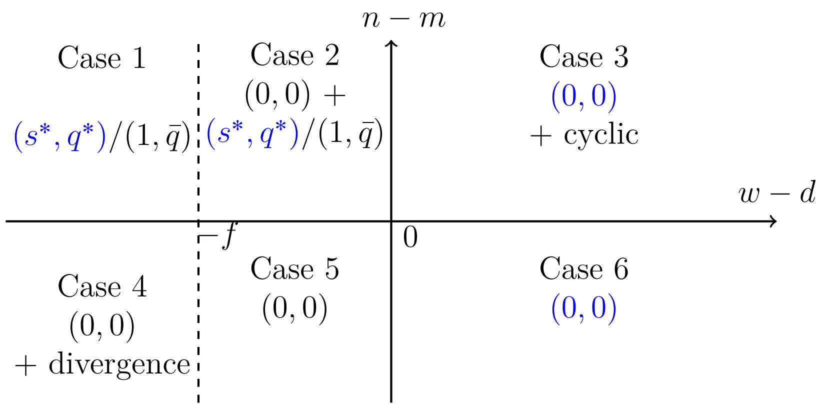

FIGURE 2.8: Summary of asymptotic states by cases

initial starting point of the system as illustrated in Figure 2.9. Such coexistence of multiple stable equilibria, which includes unsustainable $(0,0)$ equilibrium, brings instability that makes the platform vulnerable to random perturbations. Specifically, if the system is converging towards (s^*, q^*) (which could be sustainable), a random perturbation may alter the evolution trajectory and potentially push the system towards unsustainable $(0,0)$ (and consequently the platform collapses).

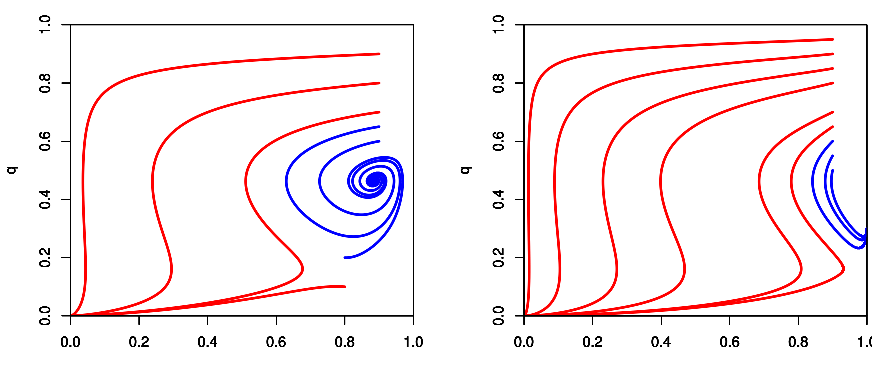

FIGURE 2.9: Coexistence of multiple stable equilibria

Case 3 and 6 are sustainable, but the social dilemma remains unresolved as the only SAS equilibrium is $(0,0)$ in which all riders are crude. However, since drivers receive positive payoffs, $w - d > 0$, such a "taxi" state (0,0) is sustainable, as long as riders would also receive positive payoffs, i.e., as long as $v - p > 0$. Hence, the platform business reduces to the traditional (and sustainable) taxi service.

Case 1 might be sustainable, depending on the asymptotically stable equilibrium. Specifically, under (s^*, q^*), all types of riders and drivers could receive positive expected payoffs (with appropriate wage w and price p), and the platform could be sustainable, i.e., (s^*, q^*) could be a SAS equilibrium.

The following is a direct consequence of Lemma 1, which establishes ways for the platform to potentially steer the system towards equilibrium (s^*, q^*) under Case 1.

Proposition 2. *Consider Case 1. The platform can potentially steer the state of the system towards the equilibrium* (s^*, q^*) *by increasing wage* $w(< p)$ *or decreasing price* p*.*

The next lemma establishes that under (s^*, q^*), the platform can further steer the system towards a potentially more socially desirable state, i.e., with higher q and lower s.

Lemma 5. q^* *and* s^* *are decreasing in* w*.* q^* *is constant in* p *and* s^* *is increasing in* p*.*

Proof. For Lemma 5, it can be easily verified that q^* and s^* are decreasing in w, and q^* is constant in p and s^* is increasing in p. It can also be easily verified that $\bar{q}(= \frac{2m(v-p-c)}{(n-m)(v-p)})$ is decreasing in p and constant in w. Thus, Proposition 2 follows from Lemma 1. □

Lemma 5 implies that *i*) when the system is in a state with a large proportion of crude riders (i.e., when q^* is low), the platform could incentivize drivers to be more selective by lowering the wage w to indirectly impose pressure on riders to be courteous (as q^* and s^* are decreasing in w); *ii*) when the system is in a state with a large proportion of selective drivers (i.e., when s^* is high), the platform, somewhat surprisingly, could lower the price p to decrease the proportion of selective drivers (s^*), without affecting the proportion of courteous riders (q^*) (as q^* is constant in p but s^* is increasing in p). Combining these two insights, the platform could simultaneously incentivize riders to be courteous and disincentivize drivers from being selective, by setting a low price p and a low wage w. This insight is somewhat consistent with the observed pricing decisions of several ride-hailing platforms (e.g., Uber and Lyft) and provides an additional alternative explanation why maintaining both low price and low wage is important for platform performance, beyond responding to competitive pressures.

In summary, as established by Theorem 1, there are only two types of SAS equilibria. Thus, the platform could either steer the system towards Case 1 by setting a sufficiently low wage (and thus price), so that the resulting SAS equilibrium resembles current successful ride-hailing platforms in which all riders may receive service (i.e., the SAS equilibrium is "ride-hailing platform" (s^*, q^*)), or, alternatively, the platform could steer the system towards Case 3 or 6 by setting a sufficiently high wage and resulting SAS equilibrium resembles a traditional taxi service (i.e.,the SAS equilibrium is "taxi" $(0, 0)$).

Note that either $(0, 0)$ or (s^*, q^*) could be more socially desirable in terms of total welfare.

Example 4. *Consider a setting with supply shortage, $m/n = 2/3$ and normalize the value of a ride to riders at $v = 1$. Let the price of service be set at $p = 0.5$, and driver's screening cost set at $f = 0.05$. Further set the damage that crude riders impose on their drivers at $d = 0.3$.*

We consider two situations differ in the degree of social dilemma (measured by $d - c$):

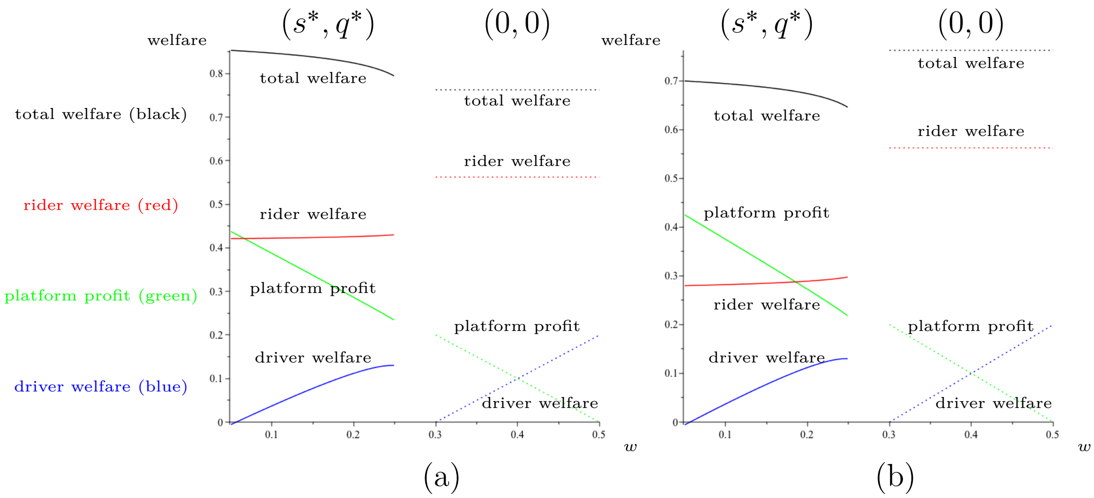

FIGURE 2.10: Welfare comparison between $(0, 0)$ and (s^*, q^*)

(a) strong social dilemma by setting the cost to riders to be courteous at $c = 0.1$ *(so that the degree of social dilemma is* $d - c = 0.3 - 0.1 = 0.2$*);*

(b) weak social dilemma by setting the cost to riders to be courteous at $c = 0.2$ *(so that the degree of social dilemma is* $d - c = 0.3 - 0.2 = 0.1$*).*

With these parameters, in both (a) and (b),

i) (s^*, q^*) *is the SAS equilibrium if driver wage* w *is set so that* $0 < w \leqslant 0.25$*;*

ii) SAS equilibrium does not exist if driver wage w *is set so that* $0.25 < w < 0.3$*,*

iii) $(0, 0)$ *is the SAS equilibrium if driver wage* w *is set so that* $0.3 \leqslant w < 0.5 = p$*.*

Figure 2.10 depicts, for both (a) and (b), the total welfare (along with rider welfare, platform profit, driver welfare) in SAS equilibrium when it exists, as a function of driver wage w*. Note that with strong social dilemma (i.e., in (a)), the total welfare is maximized in a "ride-hailing platform" SAS equilibrium (as it is better for the platform to use low wage* w *to incentivize drivers to screen riders so that they behave courteously, than to compensate drivers with high wages) which requires setting low wages for drivers. On the other hand, with weak social dilemma (i.e., in (b)), the total welfare is maximized in a "taxi" SAS equilibrium which requires setting high wages for drivers (as it is better for the platform to use high wage* w *to compensate* *drivers for damage from driving crude riders, than to let drivers incur screening cost to impose pressures on riders to make costly effort to behave courteously).* □

In summary, the key behind the comparison of the two types of SAS quilibria lies in the degree of social dilemma, which is measured by $d - c$. When the social dilemma is relatively strong ($d - c = 0.3 - 0.1 = 0.2$ in Example 3), “ride-hailing platform” SAS equilibrium is more socially desirable, i.e., (s^*, q^*) leads to a higher total welfare than $(0, 0)$ does. Whereas, when the social dilemma is relatively weak ($d - c = 0.3 - 0.2 = 0.1$ in Example 3), “taxi” SAS equilibrium is more socially desirable, i.e., $(0, 0)$ leads to a higher total welfare than (s^*, q^*) does.

2.4 Priority Matching

Note that the socially optimal (i.e., total welfare maximizing) state is $(0, 1)$, i.e., no drivers are selective, yet all the riders are courteous. Also note that the platform cannot achieve this socially optimal state in a SAS equilibrium by leveraging only price p and wage w. In this section, we consider a small adjustment of the nearest-neighbor matching scheme, so that it prioritizes courteous riders when resolving local tie-breaking. We establish that such a small adjustment of the matching protocol could allow for the emergence of the socially optimal state $(0, 1)$ as the SAS equilibrium of the system, and could increase welfare even if $(0, 1)$ is not the SAS equilibrium.

Specifically, we adjust the nearest-neighbor matching protocol, so that in the Initial Proposal stage of the protocol, a matching involving a courteous rider is given priority over a matching involving a crude rider in any neighborhood containing such pair of matches. Recall that every neighborhood contains at most two matches and there can be two riders in the same neighborhood only if $m < n$. Hence, prioritizing courteous riders within their neighborhood has no effect if there is only one rider in the neighborhood or if both riders in the neighborhood are courteous (or if both are crude).

Definition 5 (Priority Matching)**.** *The priority matching is a platform-proposed matching protocol defined by the following two stages:*

1. First Match (Initial Proposal): Platform proposes one match in every neighborhood. If there are two potential matches in the neighborhood, and only one of them involves a courteous driver, the platform proposes that match. Otherwise, both matches have equal chance of being proposed, i.e., the proposed match in the neighborhood is selected at random.

2. Second Match (Marker-clearing): If there are two potential matches in the neighborhood and if the initially proposed match was rejected, the platform proposes the other potential match in the neighborhood. Driver of a newly proposed match decides whether to accept or reject the match.

□

Note that priority matching differs from nearest-neighbor matching only in proposed matches in the Initial Proposal stage. Furthermore, the difference is confined to a neighborhood and the only neighborhoods affected are ones that contain one courteous and one crude rider. Hence, one can view the Initial Proposal stage of priority matching as a localized priority-based tie-breaking rule (in contrast to the localized random tie-breaking in the Initial Proposal stage of nearest-neighbor matching). Specifically, priority matching might differ from nearest-neighbor matching only when there can be multiple riders in a neighborhood, i.e., when there is supply shortage ($m < n$) which corresponds to Cases 1,2, and 3, only. Under the priority matching scheme, the expected payoffs for drivers and riders in Cases 1,2, and 3 are as follows.

Case 1 and 2: The respective expected payoffs for selective and non-selective drivers are

$$\Pi_D^S = ((1-\frac{n-m}{m})q+\frac{n-m}{m}(1-(1-q)^2))w-f = qw+(1-q)\frac{n-m}{m}qw-f, \quad (2.15)$$

and

$$\Pi_D^L = (q+\frac{n-m}{m}q(1-q))w + (1-q-\frac{n-m}{m}q(1-q))(w-d). \quad (2.16)$$

The respective expected payoffs for courteous and crude riders are

$$\Pi_R^A = (1-\frac{n-m}{m}q\frac{1}{2})(v-p)-c, \quad (2.17)$$

and

$$\Pi_R^B = (1-s)((1-\frac{n-m}{m})+\frac{n-m}{m}(1-q)\frac{1}{2})(v-p). \quad (2.18)$$

Case 3: The respective expected payoffs for selective and non-selective drivers are

$$\begin{aligned}\Pi_D^S &= (1-\frac{n-m}{m})qw+\frac{n-m}{m}((1-(1-q)^2)w+(1-q)^2(w-d))-f \\ &= qw+(1-q)\frac{n-m}{m}(qw+(1-q)(w-d))-f,\end{aligned} \quad (2.19)$$

and

$$\Pi_D^L = (q+\frac{n-m}{m}q(1-q))w + (1-q-\frac{n-m}{m}q(1-q))(w-d). \quad (2.20)$$

The respective expected payoffs for courteous and crude riders are

$$\Pi_R^A = (1-\frac{n-m}{m}q\frac{1}{2})(v-p)-c, \quad (2.21)$$

and

$$\Pi_R^B = s\frac{n-m}{m}(1-q)\frac{1}{2}(v-p) + (1-s)((1-\frac{n-m}{m})(v-p) + \frac{n-m}{m}(1-q)\frac{1}{2}(v-p)). \tag{2.22}$$

The next theorem establishes that the priority matching scheme could potentially steer the state of system towards the socially optimal state, $(0, 1)$.

Theorem 2. *Consider the platform that uses priority matching. The socially optimal state* $(0, 1)$ *is the unique SAS equilibrium if*

$$\frac{m}{n} < \frac{v-p}{2c+v-p}.$$

Proof. In Case 1, the equations can be written as

$$\frac{ds}{dt} = s(1-s)G_1(q),$$

$$\frac{dq}{dt} = q(1-q)G_2(s, q).$$

Here,

$$G_1(q) = -\frac{1}{a}(-w+d)(-1+a)q^2 + \frac{1}{a}(w-d)q + d - f - w$$

$$G_2(s, q) = \frac{\mu}{2a}((q+3)a - q - 1)(s - \tau(q)),$$

and

$$\tau(q) = \frac{(2c+\mu)a - \mu}{((-1+a)q + 3a - 1)\mu}.$$

Note that

$$a = \frac{m}{n}, \qquad \mu = v - p.$$

Clearly, $G_1(0) = d - f - w > 0$ and $G_1(1) = -f < 0$. Also note that the leading coefficient of $G_1(q)$ is positive. It follows that there exists a unique root q^* of $G_1(q)$ in $(0, 1)$. When $q^* < q < 1$, $\frac{ds}{dt} < 0$; when $0 < q < q^*$, $\frac{ds}{dt} > 0$.

Since the expression $(q+3)a-q-1$ is always positive given the range of our parameters, the sign of $\tau(q)$ is determined by that of $(2c+\mu)a-\mu$. If $a<\frac{\mu}{2c+\mu}$, we have $\tau(q)<0$ and therefore $s-\tau(q)>0$ for all $s,q\in(0,1)$. Clearly, $\frac{dq}{dt}>0$. It then follows that $(0,1)$ is the only asymptotically stable equilibrium.

In Case 2, the equations are the same as in Case 1. The only difference is that the condition $f<w<d-f$ is now replaced by the two conditions $f<w<d; d-w-f<0$.

Clearly, $G_1(0)=d-f-w<0$ and $G_1(1)=-f<0$. Also note that the leading coefficient of $G_1(q)$ is positive. It follows that $G_1(q)<0$ must hold for all $q\in(0,1)$.

Since the expression $(q+3)a-q-1$ is always positive given the range of our parameters, the sign of $\tau(q)$ is determined by that of $(2c+\mu)a-\mu$. If $a<\frac{\mu}{2c+\mu}$, we have $\tau(q)<0$ and therefore $s-\tau(q)>0$ for all $s,q\in(0,1)$. Clearly, $\frac{dq}{dt}>0$. It then follows that $(0,1)$ is the only asymptotically stable equilibrium.

In Case 3, the equations are

$$\frac{ds}{dt}=s(1-s)G_1(q),$$

$$\frac{dq}{dt}=q(1-q)G_2(s).$$

Here,

$$G_1(q)=(1-q)(w-d)\left(\frac{1}{a}-2\right)-f,$$

$$G_2(s)=\mu\left(\frac{3}{2}-\frac{1}{2a}-(1-s)(2-\frac{1}{a})\right)-c$$

Clearly, $(s,q)=(0,1)$ is an equilibrium. Based on the assumptions on the parameters for this case, we have $G_1(0)=(w-d)\left(\frac{1}{a}-2\right)-f<0$ and $G_1(1)=-f<0$.

Also, $G_2(0) = \left(\frac{1}{2a} - \frac{1}{2}\right)\mu - c > 0$ given $a < \frac{\mu}{2c+\mu}$. It follows that $(s, q) = (0, 1)$ is asymptotically stable. The uniqueness follows from the fact that $G_1(q)$ has no root in $(0, 1)$.

This completes the proof. □

Theorem 2 establishes that by leveraging the priority matching scheme (which includes a minimal local tie-breaking interventions in the proposed matchings), the platform could induce $(0, 1)$ as the unique SAS equilibrium, provided that drivers are in sufficiently short supply. Essentially, with drivers in short supply and with priority given to courteous riders, riders are forced to be courteous in order to receive service. Note that if the condition in Theorem 2 is not satisfied, the platform could either increase the total number of riders n (e.g., through advertising) or lower the price p. In our model, n is exogenous for tractability, however, in practice lowering the price could result in increase of n (i.e., could attract more riders to join the platform).

2.4.1 Platform Performance with Priority Matching: Numerical Simulations

Note that Theorem 2 provides a sufficient condition suggesting ways in which a platform utilizing priority matching could make other operational decisions (e.g. price adjustment) to steer the system towards the SAS equilibrium (0,1), which is socially optimal. Unlike nearest-neighbor matching (NNM) for which all stable equilibria of the system were characterized in Section 2.3, we do not have an analogous full analytical characterization of stable equilibria under priority matching (PM), due to increased complexity of analyzing the system of ordinary differential equations with PM. To further test and validate the impact of PM on the platform's performance, we conduct a series of numerical simulations as follows.

Simulation Setup

Recall that PM differs from NNM only when $m < n$, i.e., in Cases 1,2, and 3 that cover supply shortage. Further, in our simulations, without loss of generality we normalize the maximum total value in the system to be 1. Each simulation run is generated via Monte-Carlo approach, providing a random draw of parameters m/n (so that $m < n$), v, p, w (so that $0 < w < p < v$), c, d (so that $0 < c < d$ and $p < v - c$), and f (so that $f \geqslant 0$ and $w - f > 0$). We also draw starting state of the system (s^0, q^0) uniformly at random. Then, for every instance generated this way, we find the asymptotic state using NNM and the asymptotic state using PM (through standard iterative approach). Finally, we calculate total welfare, driver welfare, rider welfare and platform profit for these asymptotic states, and classify SAS equilibria if they exist. (If the asymptotic state is not sustainable, the platform collapses and in such cases we consequently record total welfare, driver welfare, rider welfare and platform profit as 0.)

Simulation Results

We run 1000 instances of the simulation. Simulation results are summarized in Table 2.1.

Table 2.1: State transitions from nearest-neighbor matching to priority matching

NNM / PM	(s^*, q^*)	$(0,1)$	$(0,0)$	unsus.	all	avg. improv.
(s^*, q^*)	121	**60**	2	10	193	0.03
$(0,0)$	0	**106**	176	17	299	0.27
unsus.	66	**62**	25	355	508	0.07
all	187	**228**	203	382	1000	0.12

Based on the simulation results, there are 465 trials that have SAS equilibria under both NNM and PM. There are 153 instances that do not have SAS equilibria (we call them *unsustainable*, denoted as “unsus.” in Table 2.1) under NNM, but do have a SAS equilibrium under PM. We say that in such instances the platform could be *salvaged* if it would switch from NNM to PM. (Note that there are 27 instances that have a SAS equilibrium under NNM but do not have it under PM.) Finally, there are 355 instances that do not have SAS equilibria under NNM nor under PM, i.e., in these instances the platform cannot be salvaged by simply switching to PM. (However, note that it is possible that in some of those instances the platform could be salvaged if it would use other instruments, e.g., adjusting price p and wage w, in conjunction with switching to PM. Hence, our analysis only points to isolated benefit of PM, while the benefit of PM is potentially larger when combined with utilizing other instruments and operational tools at the platform's disposal.)

Note that the percentage of unsustainable instances under NNM is over 50% (508 instances; recall that each instance is drawn uniformly at random, hence this percentage can be interpreted as a probability estimate of a system drawn at random not being asymptotically sustainable), but it drops significantly (38.2% corresponding to 382 instances) under PM. Also note that 22.8% have the social optimum, i.e., total welfare maximizing state $(0, 1)$, as their unique SAS equilibrium. Recall that $(0, 1)$ cannot be SAS equilibrium under NNM, as established by Theorem 1. Hence, for these instances, using PM instead of NNM, ensures significant improvement in total welfare. Specifically, average improvement (not reported in Table 2.1) is 0.35, corresponding to the total welfare (i.e., efficiency) increasing by at least 35% on average (because total value of the system is normalized at 1). Finally note that switching to PM improves total welfare, regardless of the asymptotic state of the system under NNM, as reported in "avg.improv." column of Table 1. Overall, switching from NNM to PM increases total welfare by 12% on average.

We next further analyze how total welfare improvements due to switching to PM from NNM are distributed among drivers, riders and the platform. We start by depicting starting states of our 1000 simulation instances in Figure 2.11. The four charts of Figure 2.11 illustrate the welfare after the system converges to the asymptotic state under NNM. The x-axis is s, the proportion of selective drivers, and the y-axis is q, the proportion of courteous riders. The dots on the plots in Figure 2.11 correspond to 1000 starting points (s^0, q^0), one for each simulation instance. The

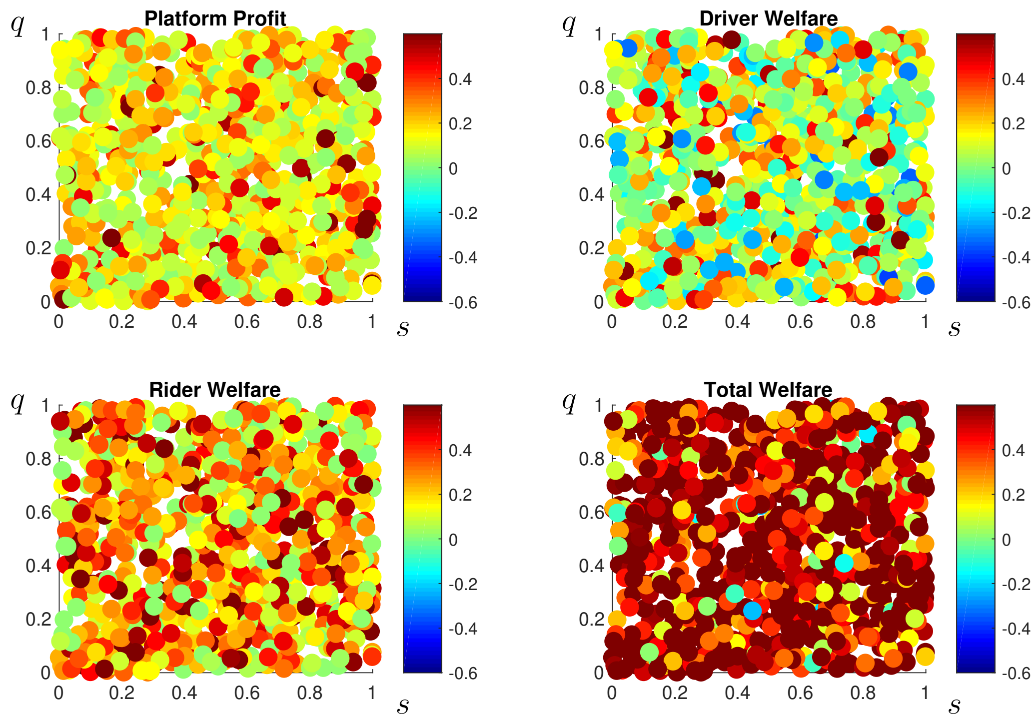

FIGURE 2.11: Welfare: starting points

colors of the dots indicate the welfare values (if negative, the platform collapses). (Note that dots on Figure 2.11 fill the unit square, due to the way how starting points (s^0, q^0) are generated in our simulation.) In a similar fashion, dots on the plots in Figure 2.12 correspond to SAS equilibria under NNM. Thus, each chart of Figure 2.12 contains only 492 dots, with the dot at $(0, 0)$ corresponding to 299 instances. Note that, even though starting points (s^0, q^0) fill the entire square, not all points in the unit square are equally likely to be SAS equilibria under NNM. (For example, by Theorem 1 we know that $(0, 1)$ cannot be a dot in Figure 2.12. Interestingly, Figure 2.12 suggests that SAS equilibrium under NNM is more likely when q is large, i.e., riders are more likely to be courteous than crude in equilibrium.) Also notice that Driver Welfare chart of Figure 2.12 suggests that driver welfare increases from the bottom (where q is low) to the top (where q is high). Similarly,

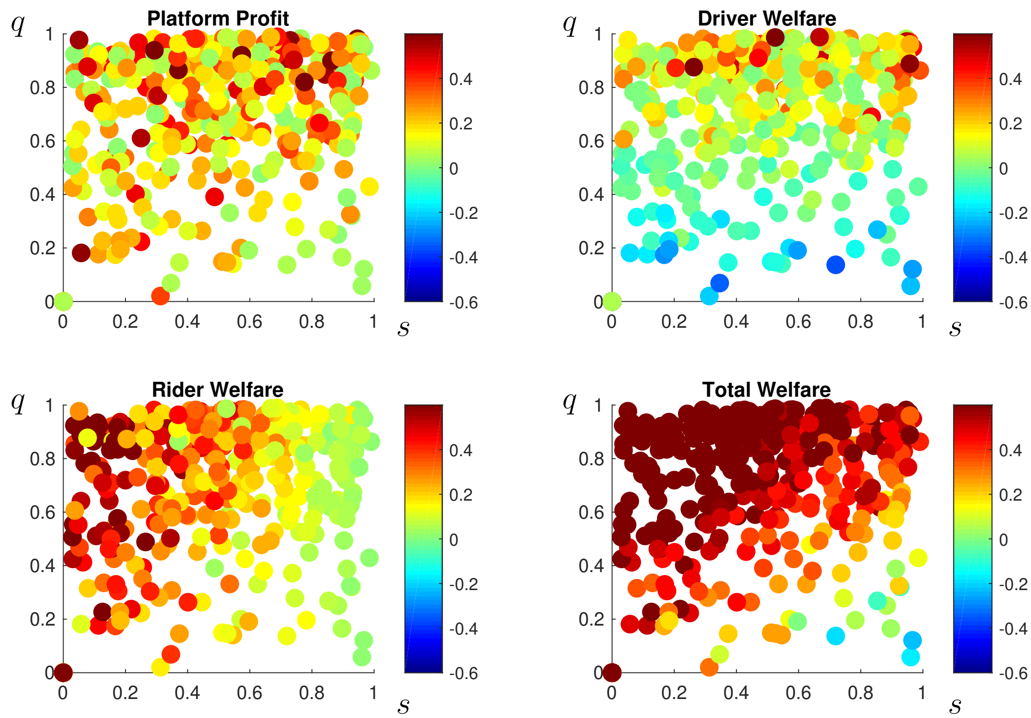

FIGURE 2.12: Welfare: NNM equilibria

Rider Welfare chart of Figure 2.12 suggests that rider welfare increases from the right (where s is high) to the left (where s is low). Finally, Total Welfare chart of Figure 2.12 combines the trends of driver welfare and rider welfare, i.e., the chart suggests total welfare increases from the bottom right corner (where s is high and q is low) to the top left corner (where s is low and q is high).

Figure 2.13 and 2.14 illustrate welfare improvements if the platform switches from nearest-neighbor matching to priority matching, providing depictions from two different perspectives: perspective of SAS equilibria under NNM (Figure 2.13) and perspective of SAS equilibria under PM (Figure 2.14). More precisely, each dot corresponds to an instance of our simulation. The position of the dot corresponds to the coordinates of SAS equilibrium under NNM (Figure 2.13) or under PM equilibrium (Figure 2.14). Color of a dot represents the difference between welfare (platform

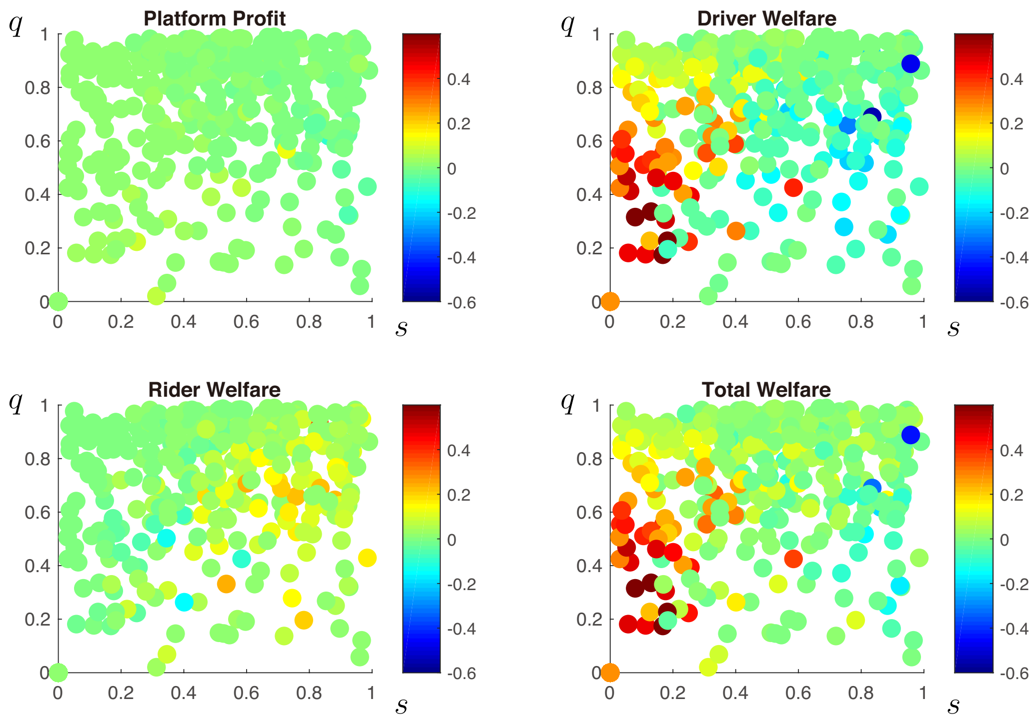

Figure 2.13: Welfare improvement of switching from NNM to PM: NNM equilibria

profit, driver welfare, rider welfare, total welfare) in the SAS equilibrium under PM and the corresponding welfare in the SAS equilibrium under NNM, for an instance of our simulation run. (Recall that if the instance is unsustainable under NNM or PM, the corresponding welfare is recorded as 0.) Thus, there are 492 dots in each chart of Figure 2.13, and, e.g., dot at $(0, 0)$ represents average welfare difference of 299 instances that have $(0, 0)$ as the SAS equilibrium (which is 0.27 for total welfare, as reported in Table 2.1). Similarly, there are 618 dots in each chart of Figure 2.14, and, e.g., dot at $(0, 1)$ represents average welfare difference of 228 instances that have $(0, 1)$ as the SAS equilibrium (which is 0.35 for total welfare, as mentioned earlier).

Platform Profit and Rider Welfare charts of Figure 2.13 and 2.14 suggest that platform profit and rider welfare are mostly unaffected by switching from NNM to PM. However, Driver Welfare and Total Welfare charts of Figure 2.13 suggest that

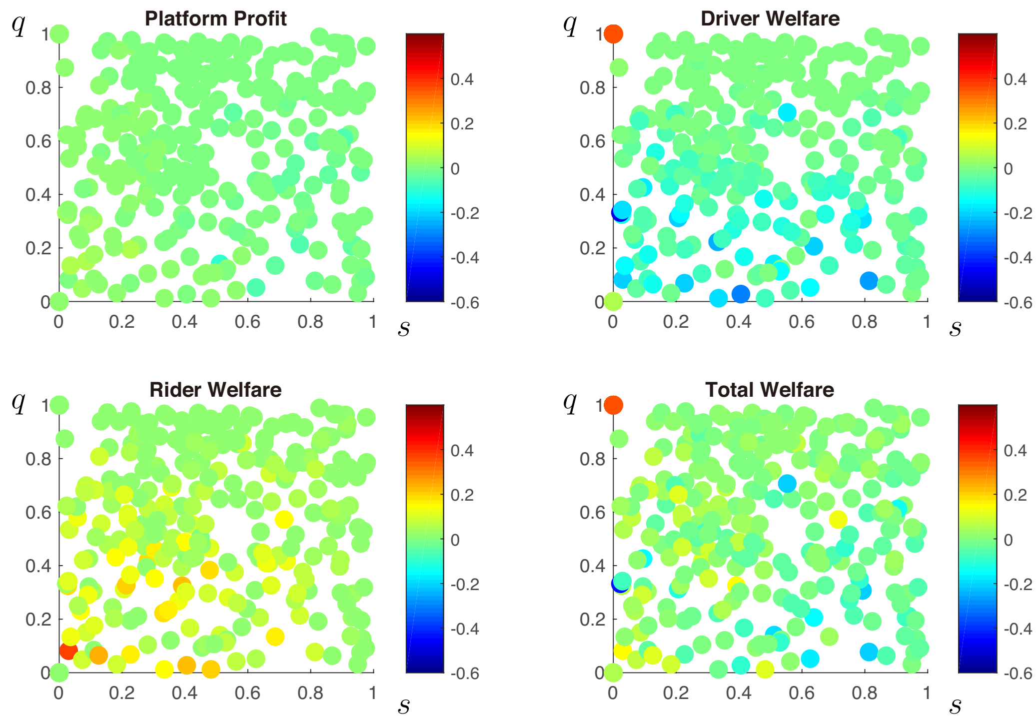

FIGURE 2.14: Welfare improvement of switching from NNM to PM: PM equilibria

switching from NNM to PM could increase driver welfare and total welfare. More specifically, these charts suggest that driver welfare and total welfare increase the most at the bottom left corner of the plots where the proportion of courteous riders is low (i.e., q is small) and the proportion of selective drivers is also low (i.e., s is small). Note that this implies that in the situations where drivers are not selective enough (due to high cost of being selective) and thus riders' conduct is not properly incentivized, the direct intervention of the platform in the form of switching to PM, could potentially alleviate the social dilemma and improve the welfare of drivers and the entire system. Finally, charts of Figure 2.14 suggest that the largest welfare improvements are realized if $(0, 1)$ is the SAS equilibrium under PM (corresponding to 228 instances in our simulation). Note that this numerically corroborates findings of Theorem 2 and shows that the condition of Theorem 2 is satisfied for a large proportion of initial parameters of the system.

2.5 Concluding Remarks

In this chapter we show that user behavior has a profound impact on ride-hailing platform's performance. Specifically, we develop an evolutionary game theory model to study the evolution of user behavior, and show that incentivizing riders to make an effort not to impose negative externalities on drivers during service is of critical importance to the platform. Moreover, we discuss ways how the platform can shape user behavior in order to steer the system towards a state which guarantees not only improvements in the platform's stability and sustainability, but also improvements in the social welfare.

The critical tradeoffs we analyze and exploit are different for riders and drivers. Riders face the tradeoff between making a costly effort not to impose negative externality on their driver (e.g., by being ready at the correct pick-up location when driver arrives), and avoiding the cost of this effort but imposing a negative externality on their driver, whose payoff will be reduced due to such rider behavior. On the other hand, drivers face the tradeoff between accepting a ride which might result in negative externalities being imposed on them, and incurring cost to check rider ratings before deciding whether to accept or reject the platform-proposed ride. From the societal perspective, it is optimal for riders not to impose negative externalities to their drivers (provided that the cost of their effort is lower than the negative externalities they impose on their driver), and for drivers not to incur costs of screening riders. We show that the platform can improve its performance and facilitate proper non-monetary transfers in the sense of incentivizing riders to make a costly effort and not impose negative externalities on drivers. Essentially, riders pay for the service in part through the cost of their effort, while drivers are paid for providing service in part through avoiding negative externalities that could have been imposed on them (e.g., minimize idle time due to excessive waiting time).

Our principal methodological contribution is that we model dynamics of the platform using an evolutionary game theory model. We are able to characterize all asymptotically stable equilibria of this system which allow us to establish that, absent platform's discrimination of riders who choose not to make a costly effort, the platform cannot be steered towards a socially optimal (total welfare maximizing) state. Specifically, a ride-hailing platform can be in only two sustainable asymptotically stable states: (a) "taxi" state in which all riders impose negative externalities on their drivers, but the system is sustainable to high wages (that are needed to compensate drivers for the negative externality they need to absorb), and (b) a state reminiscent of successful ride-hailing platforms in which riders and drivers resolve their respective tradeoffs either way with non-zero probability. The latter state only partially resolves the social inefficiencies of negative externalities imposed on drivers, but there are sufficient incentives in place for riders to behave in a socially desirable way. Furthermore, we establish that this SAS equilibrium is supported and enhanced by low wages for service providers and low service prices (thereby partially unlocking aforementioned non-monetary transfers). Our analysis provides an analytical explanation, in the form of the unique sustainable asymptotically stable equilibrium of the dynamic system, for prevalence of low wages and low prices in ride-hailing services (and, more generally, in other on-demand economy service platforms).

We also show that the platform could utilize riders' ratings to incentivize them to make costly efforts, and consequently steer the system towards the socially optimal state. This could be achieved by a minimal adjustment in the matching procedure and it only requires prioritizing riders who make costly effort in the cases when tie-breaking among riders is needed to find the best local match. (Note that price discrimination of riders for identical rides is highly non-practical and could possibly be implemented only sporadically by limited targeted discounts.) Hence, the analysis of our model suggests that the ride-hailing platform adds value not just by its dispatching ability (i.e., quality of the matching algorithm), but also by incentivizing users to resolve the social dilemma by avoiding social inefficiencies (due to riders imposing negative externalities to drivers), and in doing so improving its performance.

3

Managing Innovation Spillover in Sourcing

3.1 Introduction

In the past decades, the dominant trend in manufacturing has been vertical disintegration and outsourcing. Firms have increasingly specialized in their core competences and depended on suppliers for other value-adding processes. One indicator of this trend is the growth of global business-to-business trades, which had reached $60 trillion in 2000 (Kshetri and Dholakia, 2002). To put this figure in perspective, the US GDP in the same year was $10 trillion (The World Bank, 2015). This transformation elevates the once clerical function of sourcing to a strategic level where many important considerations must be accounted for in the decision-making process. One such issue which has attracted much attention is knowledge spillover, namely that through sourcing-related interactions between a firm and its supplier, some of the firm's valuable knowledge is inevitably transferred to the supplier. For example, Foxconn which manufactures electronic devices for clients raises concerns about technology spillover (Hsiao et al., 2016); Apple, a leader in the smartphone market, and Samsung, one of Apple's most important suppliers for smartphone components, had filed over 50 patent lawsuits against each other as of 2015 (Elmer-DeWitt, 2015).

This phenomenon has been studied in the sourcing literature from different perspectives. Knowledge spillover is painted in a positive light when the knowledge obtained by the supplier helps improve its efficiency or yield (Kotabe et al., 2003). On the other hand, knowledge spillover may be painted in a negative light if it somehow benefits a competitor—either a competing firm that sources from the same supplier (Qi et al., 2015; Agrawal et al., 2016), or the supplier itself if it also competes with the buying firm in the market (Chen and Chen, 2014).

The majority of the literature on spillover in sourcing studies *technology* spillover, where the transferred knowledge is about an existing and proven technology and is assumed to be of a known value for the supplier (e.g., Chen and Chen 2014). This is a reasonable assumption about technology spillover because such technologies can usually generate measurable and predictable improvements of the latter's manufacturing process. On the other hand, many firms experience *innovation spillover* to or through suppliers, where the transferred knowledge is about a new product feature yet to be introduced in the market. Because the value of such an innovation is rooted in consumer experiences, it may not be accurately estimated prior to the product launch; actually the eventually realized value may even be negative if the new feature is poorly received. In this chapter we focus squarely on studying innovation spillover in sourcing. Our focus necessitates assuming the values of innovations to be ex-ante uncertain and only realized after the product launch. This setting differentiates our work from most related literature on technology spillover in sourcing.

A class of innovations are driven by technological developments, where new technologies enable enhanced functionalities of product features. For example, the high-resolution Retina Display in Apple's iPhone 4 provided sharp and clear images (Apple, 2010), and the 3D Touch feature in Apple's iPhone 6s added force sensitivity to the touchscreen (Apple, 2015). Such technical innovations usually require close collaborations with suppliers during the development stage.[1] For example, iPhone 4's Retina Display had the highest resolution to date in a phone (iMore, 2015) and Apple worked closely with LG to achieve the technical feat (CNET, 2010). In the collaboration process, the innovator's knowledge about the innovation inevitably spills over to its supplier. On the other hand, for a competitor not involved in the development process of a technical innovation, it is difficult to immediately imitate the innovation after the product is launched, because the competitor would need to independently develop the technology which would take substantial time. In the case of the iPhone 4 with the Retina Display, it took 1.5 years (more than an entire model iteration) for the first competitor phone, Google and Samsung's Galaxy Nexus, to surpass its pixel density (Engadget, 2011).

By contrast, another class of innovations are not primarily driven by new technologies, but by innovative designs using existing technologies. To give another iPhone example, one of the original iPhone's definitive innovations was a touchscreen user interface without a regular physical keyboard. The touchscreen technology was not new (Erickson, 2012), and Apple's then-CEO Steve Jobs in the product launch exclusively focused on interaction designs such as touch gestures rather than the technology behind it (Apple, 2017). (The full-touchscreen user interface was also a perfect example of the ex-ante uncertain and even possibly negative value of an innovation. The design was initially controversial, with several early reviews concluding that the touchscreen offers inferior experiences to a physical keyboard; e.g., PC World 2007.) For such non-technical innovations, their values are primarily driven by the designs. The innovations still spill over to suppliers involved in the development process, although they do not heavily depend on the suppliers' capabilities. As a result, once a product carrying a non-technical innovation is launched, it is relatively

[1] In other cases innovators develop technical innovations internally, but such cases are irrelevant for our study of innovation spillover in sourcing.

easy for competitors to quickly imitate the innovation. A good example is Google's Android smartphone, which as a 2007 prototype was modeled after a BlackBerry, yet clearly resembled the iPhone when shipped in 2008, only months after the latter's successful launch (Technobuffalo, 2011).

It is worth noting that innovative firms such as Apple view innovations as their primary source of competitive advantage, and in most cases attempt to prevent imitations of such innovations through legal means such as patents. Unfortunately, legal efforts are not always effective. First, "abstract ideas" cannot be patented (uspto.gov, 2015); only their implementations can be patented, yet implementations are often easy to circumvent (Meland, 2006). Moreover, even granted patents do not necessarily provide protection in practice. Patent litigation procedures are extremely lengthy and costly (CNET, 2012), yet a study shows that only 9% of patent assertions were able to establish liability (Business Insider, 2014). As a result, despite potential legal protections, the reality is that innovations are frequently imitated by competitors. For example, despite Apple's maximum legal efforts to protect the iPhone's innovative gesture-based multi-touch interactivity (CNET, 2011), almost all later smartphones adopt the same design. In this work, we focus on cases where competitor imitation cannot be prevented through legal efforts, and study how innovators should manage innovation spillover in sourcing.

Innovation spillover through sourcing is particularly concerning if the supplier also competes with the innovator in the end market (which we refer to as a *competitor-supplier* in this chapter). There is no shortage of examples of such market structures. Acer manufacturers laptop computers for Hewlett-Packard and Dell while marketing its own competing products (Forbes, 2009). Samsung is one of the most important suppliers for Apple's iPhone, while also being one of the latter's most prominent competitors in the high-end market (Forbes, 2016). Given innovation spillover through sourcing, a competitor-supplier has early access to the innovation and may imitate it and market a similar product alongside the innovator. As such, should the innovator ever source from a competitor-supplier in the presence of innovation spillover? If so, would the competitor-supplier immediately imitate the innovation or delay the decision until after learning its exact value? Could the innovator take advantage of the competitor-supplier's imitation timing preference and actually benefit from innovation spillover? Do the answers differ for technical and non-technical innovations? These questions are driven by the ex-ante uncertain values of innovations and thus have not been answered in the literature focusing on technology spillover.

To answer our research questions, we model an innovator choosing between a competitor-supplier and a non-competitor supplier to develop and source an innovative product. The competitor-supplier produces a regular product, but will be able to produce the innovative product through innovation spillover, and competes with the innovator in the end market. The innovation's "value" allows the innovative product to carry a price "premium" in the market, although the "value" and thus "premium" is ex-ante uncertain and may even be negative. The non-competitor supplier does not compete with the innovator in the market. We analyze two variations of the model to capture the key difference between technical and non-technical innovations as discussed earlier: a technical innovation can only spill over through sourcing, whereas a non-technical innovation can spill over through sourcing as well as in the market. We find that for both types of innovations, the innovator may strategically source from the competitor-supplier (namely when the latter carries no explicit advantage than the non-competitor supplier). More interestingly, the strategic motivations of sourcing from the competitor-supplier for technical and non-technical innovations are polar opposites. Roughly speaking, for technical innovations the innovator may source from the competitor-supplier so that the latter would postpone launching the innovative product; and for non-technical innovations the innovator may source from the competitor-supplier so that the latter would immediately launch the innovative product alongside the innovator. The fact that distinct insights can result from a single difference in spillover channels highlights the richness of, and may potentially inform strategic sourcing decisions under innovation spillover risks.

The rest of this chapter is organized as follows. Section 3.2 provides a review of related literature. In Section 3.3 we introduce our base models which are analyzed in Section 3.4. Section 3.5 contains three models extensions which confirm the robustness of the main insights. Section 3.6 provides concluding remarks.

3.2 Literature review

Our work is related to the extensive literature on technology and innovation management in the field of operations management. Gaimon (2008) provides a comprehensive review of this literature. The review covers a wide range of topics, most different from that of our work. Erat and Kavadias (2006) and Erat et al. (2007) consider technology providers developing and selling technologies to end-product manufacturers. Wang and Shin (2015) study the impact of supply chain contracts with an upstream supplier investing in innovation and a downstream manufacturer selling to consumers. Xiao et al. (2014) and Özkan-Seely et al. (2015) study knowledge management and transfer in new product development processes. A series of papers by Krishnan and Zhu (2006), Ramachandran and Krishnan (2008) and Krishnan and Ramachandran (2011) investigate managing sequential innovations. A series of papers by Chen et al. (2013), Chen et al. (2017) and Lu et al. (2017) study co-product technologies in supply chains. In our work, we compare technical and non-technical innovations from the perspective of spillover channel.

There is a large literature on sourcing under competition and supplier encroachment (e.g., Arya et al., 2007, 2008; Ha and Tong, 2008; Lim and Tan, 2010; Ha et al., 2011; Chen et al., 2012; Feng and Lu, 2012; Li et al., 2013, 2015; Pun and Heese, 2014; Wang et al., 2014; Lin and Chen, 2015; Niu et al., 2015; Bolandifar et al., 2016;

Chu et al., 2016; Li et al., 2018; Niu et al., 2018; Chen and Chen, 2014). Arya et al. (2007), Lim and Tan (2010), Chen et al. (2012) and Wang et al. (2013) are early examples of studies in coopetitive settings where a firm sources from a supplier with which it also competes in the market. Niu et al. (2015) and Niu et al. (2018) follow up to study similar settings with new emphases on price competition, and demand uncertainty and quick response, respectively. Our work develops this literature by studying strategic sourcing decisions involving a competitor-supplier under innovation spillover. The most closely related paper to ours is by Chen and Chen (2014) who study a similar topic under spillover of technologies of known values, whereas we focus on spillover of innovations which carry ex-ante uncertain values and drive very different insights. More remotely related are papers by Harhoff (1996) who considers a setting where technology spillover takes place from suppliers to buyers, and by Qi et al. (2015) and Agrawal et al. (2016) who consider settings where technology spillover takes place between competitors through shared suppliers.

Another important element of our model is timing. Production timing or time-to-market as firms' endogenous decisions have been studied in the economic literature (e.g., Gal-Or, 1985; Saloner, 1987; Hamilton and Slutsky, 1990; Maggi, 1996; Bhaskaran and Ramachandran, 2007) and the operations literature (e.g., Ramachandran and Krishnan, 2008; Wang et al., 2013). A stream of research focusing on the value of postponing operational decisions in order to incorporate latest market conditions includes Van Mieghem and Dada (1999); Anand and Girotra (2007); Goyal and Netessine (2007), and Swinney et al. (2011). Our model is novel in connecting innovation spillover, value uncertainty and production timing through sourcing. In particular, the innovator, through its sourcing decision, can influence the competitor-supplier's decision to learn market preferences and thus its production timing. This feature is absent in the majority of the postponement literature, with the notable exception of Ülkü et al. (2005) who show that a Contract Manufacturer's capacity investment timing decision may be affected by Original Equipment Manufacturers' make-or-buy decisions, although their model is very different from ours.

One of our main results is that an innovator may strategically source from a competitor-supplier in exchange for market leadership. A similar result by Pacheco-de Almeida and Zemsky (2012) shows that an innovator may expose its intellectual property to induce rival imitation which slows down competition. However, they consider marketplace innovation spillover and assume that imitation always leads to delayed operational decisions such as production and market entry. By contrast, we consider innovation spillover in the development and sourcing stage where imitation does not necessarily lead to delayed production decisions, and show that a competitor-supplier may willingly delay its production decision if it imiates the innovation. The different problem setting and results set our work apart from that by Pacheco-de Almeida and Zemsky (2012).

3.3 Base models

We consider a non-repeated game with three firms: an innovator V, a competitor-supplier C, and a non-competitor supplier S. The innovator V is developing an innovative product and is committed to bringing it to the market at a set time. The product requires collaboration with and sourcing a key component from either C or S. The competitor supplier C also competes with V in the end market, whereas S does not compete with V. In order to isolate and focus on strategic considerations other than cost, we assume the same exogenous sourcing price w from both C and S, and the same normalized unit production cost 0 for both regular and innovative products produced by both V and C. Extensions to relax these simplifying assumptions are straightforward. We also assume that V and C will each market a single product motivated by the competition between Apple and Samsung's flagship products. This allows us to drive the clearest insights about innovation spillover without being distracted by secondary complications.

The game has three stages: Sourcing, Launch, and Competition. The Sourcing stage represents the period when V develops the innovative product with a supplier and the subsequent sourcing and production of the product, which is usually in the same order of magnitude as the length of a product cycle. In the Sourcing stage, the value of V's innovation, π (explained later), is a random variable with cumulative distribution function F over a finite support, mean $\mu \geqslant 0$, and variance σ^2, and V determines whether to collaborate with and source from C or S (in our model dual-sourcing offers no advantage), as well as the output quantity q_V of the innovative product. If V sources from C, spillover takes place and C acquires the knowledge of the innovation and may choose what product (innovative or regular) to produce and then output quantity q_C alongside V in the Sourcing stage. If V sources from S, C can only produce the regular product in the Sourcing stage. In both cases, C may also postpone the product choice and output quantity decision until the Launch stage.

The Launch stage represents the initial period following V's launch of its innovative product in the market, which is usually a relatively small part of the product cycle. In the Launch stage, the market's reaction is revealed and the innovation's value π is realized. For technical innovations, if C is V's supplier and decided to postpone its product choice and output quantity decision until the Launch stage, it now has the advantage of making these decisions after observing the realization of π and still being in time for the majority of the product cycle, but also bears the disadvantage of doing so after V. If C is not V's supplier, it would not be able to imitate V's innovation even if it postponed the product choice decision due to the technological barrier. However, for non-technical innovations, regardless of whether C is V's supplier, C would be able to produce and market the innovative product if it chose to postpone these decisions in the Sourcing stage.

Finally, the Competition stage represents the majority of the product cycle during which V and C's products compete in the Cournot fashion. We adopt the Cournot model because it can capture the impact of production decision timing between competitors while remaining tractable; it is the canonical model for this purpose (e.g., Swinney et al. 2011, Wang et al. 2013). Note that although V and C's production decision timing may be slightly different, their products coexist and compete in the market for the majority of the product cycle, thus justifying the Cournot model. In particular, we assume that given the outputs q_V and q_C, the market price for a regular product is assumed to be $a - q_V - q_C$, and the market price for an innovative product is assumed to be $a + \pi - q_V - q_C$. (This base model implies perfect substitution between regular and innovative products for tractability. An extension to imperfect substitution is explored in Section 5.3.) One can see that π measures the price "premium" of an innovative product and is thus interpreted as the "value" of innovation, although the "value" may be negative per our discussion in the Introduction. Throughout the chapter we require $a > \max\{3w, 2(\mu - w)\}$, namely the market is sufficiently lucrative, to ensure positive outputs and rule out uninteresting cases.

Below we elaborate on the specific models and timelines for technical and non-technical innovations.

3.3.1 Technical innovations

For technical innovations that can only spill over through sourcing, we denote the mean and variance of π when sourcing from C and S by μ_C, μ_S and σ_C^2, σ_S^2, respectively. (No information about higher moments is needed in our base models.) We define $\alpha \doteq \mu_C/\mu_S$ to indicate C's relative capabilities compared with S. In Sections 3.1 and 4.1 we simplify the technical innovation model by assuming that the innovation's value π cannot be negative. This simplification allows clearer presentation of results and is motivated by the observation that technical innovations tend to enhance or add features without replacing existing features (see Section 1); we later show in Section 5.1 that the key insights remain valid without this simplification.

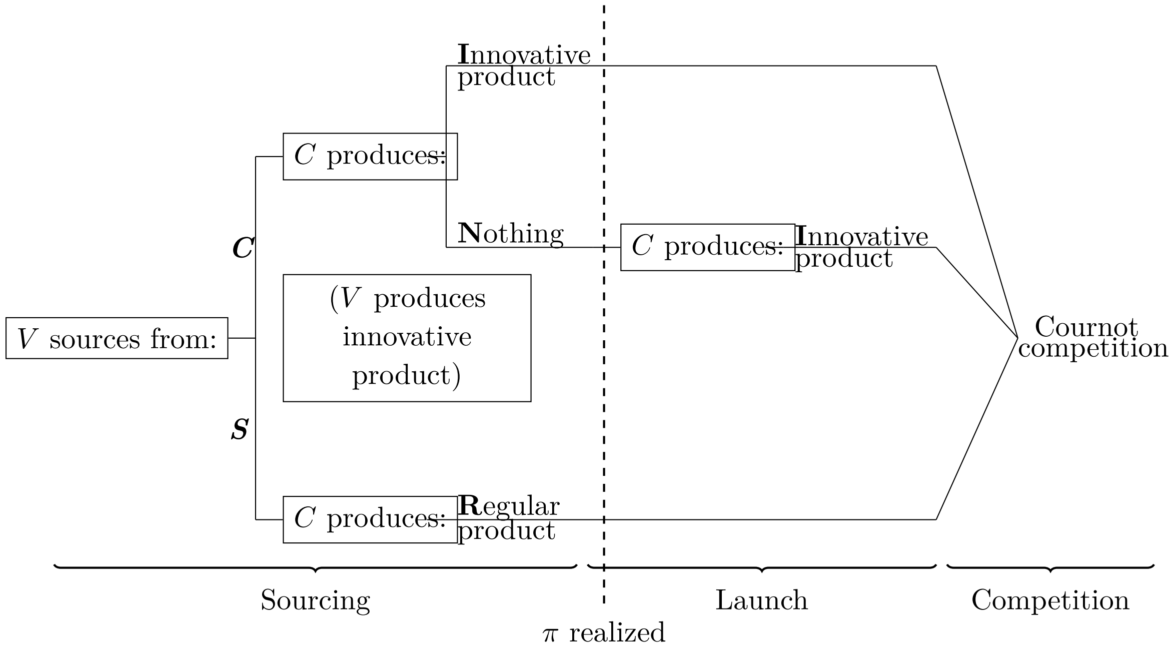

FIGURE 3.1: Game tree for technical innovations

Figure 3.1 illustrates the game tree for the simplified technical innovation model. In the Sourcing stage, V chooses to source from C or S. If V sources from C, innovation spillover occurs and C has the option to produce the innovative product at the same time as V during the Sourcing stage, before learning the innovation's value π. (In principle C may also produce the regular product at this time, but doing so provides no benefit to C because the technical innovation is assumed to have a non-negative value.) Another option of C is to postpone the decision. If V sources from S, C will simply produce the regular product at the same time as V. (In principle C may also postpone production of the regular product, but doing so provides no benefit to C.) In the Launch stage, the innovative product is revealed to the public and the value of π is realized. If C is V's supplier and postponed production, in this stage C will produce the innovative product after learning the realized value of π, albeit at the cost of choosing the production quantity after V. (In principle C may also produce the regular product at this time, but doing so provides no benefit to C because the technical innovation is assumed to have a non-negative value.) Finally, in the Competition stage, V and C's products enter the mass market and compete in the Cournot fashion, with each innovative product enjoying price premium π.

3.3.2 Non-technical innovations

For non-technical innovations that can spill over through sourcing as well as in the market, in Sections 3.2 and 4 we simplify the model by assuming that the sourcing decision does not affect the innovation's value π, and denote its mean and variance respectively by μ and σ^2 regardless of the supplier. This simplification allows clearer presentation of results and is motivated by the observation that non-technical innovations are primarily defined by the designs and do not heavily depend on supplier capabilities (see Section 1); we later show in Section 5.2 that the key insights remain valid without this simplification. We require $\mu > (a - 2w)/7$ to rule out the uninteresting case where C never imitates V's innovation after its launch. It is useful to define $\pi_+ \doteq \max\{\pi, 0\}$, and denote its mean and variance respectively by μ_+ and σ_+^2. Clearly, $\mu_+ > \mu$ and $\sigma_+^2 < \sigma^2$. We further define $\Delta\mu \doteq \mu_+ - \mu$ which captures the value of learning π before the production decision and avoiding imitating an unpopular innovation with $\pi < 0$. We require $\mu_+ < 2\mu$ or equivalently $\Delta\mu < \mu$ to ensure that V is not exposed to so great a risk due to its innovation being unpopular that it will no longer innovate.

Figure 3.2 illustrates the game tree for the simplified non-technical innovation model. The tree differs from the technical innovation tree in two additional branches (highlighted with thick lines). The first additional branch is that if V sources from C and C postpones the production decision, after learning the realized value of π, C may still choose to produce the regular product if the realized value of π

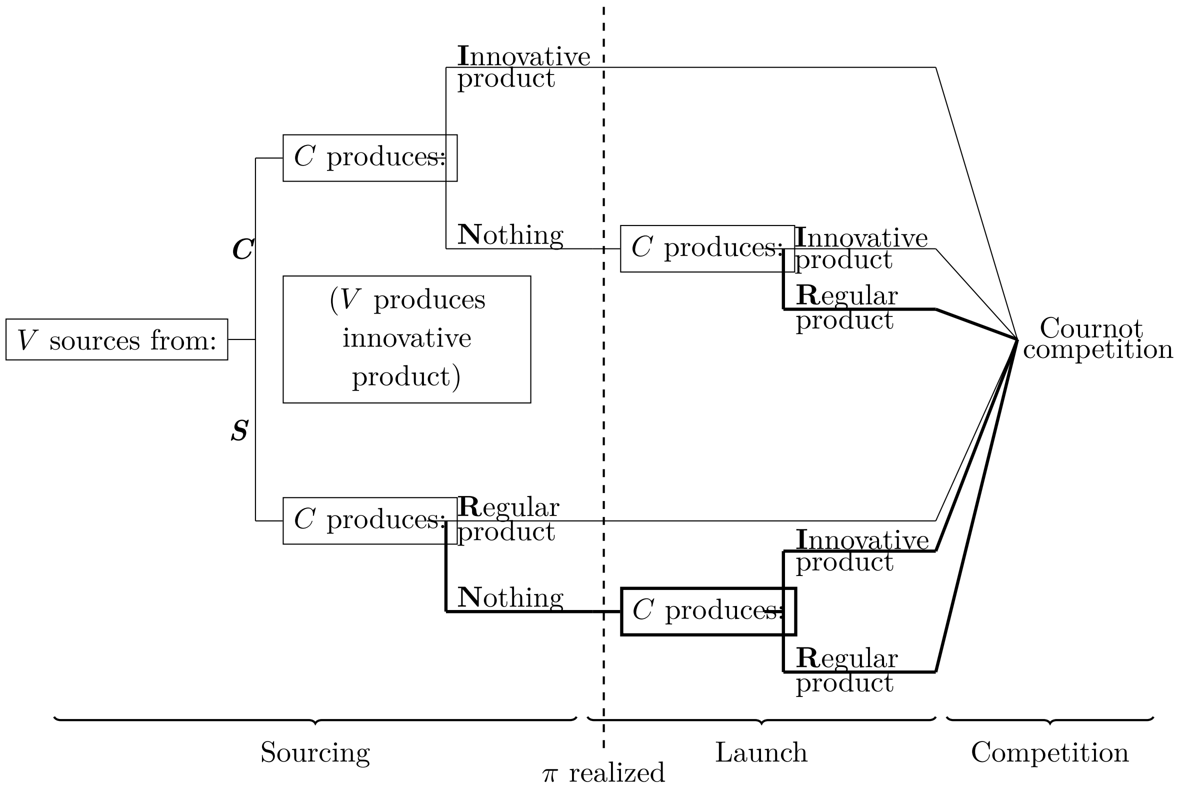

FIGURE 3.2: Game tree for non-technical innovations

of the non-technical innovation is negative. The second additional branch is that when V sources from S, C may still choose to postpone the production decision until the Launch stage. This is because unlike technical innovations, a non-technical innovation can spill over to C in the market even if C is not V's supplier. It is also worth noting that if V sources from C, C always prefers to produce the innovative product rather than the regular product at the same time as V: although the value of π may be negative, its expectation μ is positive.

3.4 Model analyses

We use the first letter of each decision branch (emboldened in Figures 3.1 and 3.2) to indicate scenarios. For example, for technical innovations, scenario CNI indicates that V sources from C, C produces nothing in the Sourcing stage, then later produces the innovative product in the Launch stage. Given each scenario, there is another layer of decision making in a production game. For example, in scenario CNI, V chooses the production quantity q_V for the innovative product in the Sourcing stage, and then C choose the production quantity q_C for the innovative product in the Launch stage, before both outputs determine the firms' profits in the Competition stage. (Similar two-layer structures have been utilized in the literature; see Swinney et al. 2011 for an example.) Let Π_X^{Scenario} denote the expected (with respect to random variable π) equilibrium profit of firm X in the Scenario's production game. For example, $\Pi_C^{C\text{NI}}$ denotes C's expected profit in the Sourcing stage, should V source from C and C choose to postpone production until the Launch stage, where the production quantities form an equilibrium in the production game. The production game can be solved relatively straightforwardly, and we focus on comparing the firms' expected profits in each scenario to analyze the equilibrium of the grand game of sourcing and product choices.

3.4.1 Technical innovations

In the simplified technical innovation model, recall that π has mean and variance μ_C, σ_C^2 and μ_S, σ_S^2 when sourcing from C and S, respectively; that w stands for the exogenous sourcing cost regardless of the supplier; and that the market price for a regular product is $a - q_V - q_C$ and that for an innovative product is $a + \pi - q_V - q_C$.

Lemma 6. *For technical innovations, the Sourcing-stage expected equilibrium profits of the production game for all possible scenarios are*

$\Pi_V^{CI} = (a + \mu_C - 2w)^2/9, \quad \Pi_C^{CI} = (a + \mu_C + w)^2/9 + w(a + \mu_C - 2w)/3,$

$\Pi_V^{CNI} = (a + \mu_C - 2w)^2/8, \quad \Pi_C^{CNI} = (a + \mu_C + 2w)^2/16 + \sigma_C^2/4 + w(a + \mu_C - 2w)/2,$

$\Pi_V^{SR} = (a + 2\mu_S - 2w)^2/9, \quad \Pi_C^{SR} = (a - \mu_S + w)^2/9.$

Proof. We derive the ex-ante expected profits of V and C in outcome CI, CNI and

SR. Let q_V and q_C denote the production quantities of V and C, respectively.

<u>Outcome CI:</u>

V sources from C, and C produces the innovative product in the Sourcing stage prior to the realization of π. The ex-ante expected profits of V and C are

$$\Pi_V^{CI} = (\mu_C + a - q_V - q_C)q_V - wq_V, \quad \Pi_C^{CI} = (\mu_C + a - q_V - q_C)q_C + wq_V. \quad (3.1)$$

By the first order condition, (3.1) yields the best responses of V and C as

$$BR_V(q_C) = (\mu_C + a - w - q_C)/2, \quad BR_C(q_V) = (\mu_C + a - q_V)/2. \quad (3.2)$$

Solving $BR_V(q_C)$ and $BR_C(q_V)$ from (3.2) jointly, we obtain the optimal output quantities

$$q_V = (a + \mu_C - 2w)/3, \quad q_C = (a + \mu_C + w)/3. \quad (3.3)$$

Plugging in the optimal quantities q_V and q_C from (3.3) into (3.1), the resulting optimal ex-ante expected profits are

$$\Pi_V^{CI} = (a + \mu_C - 2w)^2/9, \quad \Pi_C^{CI} = (a + \mu_C + w)^2/9 + w(a + \mu_C - 2w)/3. \quad (C\text{I})$$

<u>Outcome CNI:</u>

V sources from C, and C produces the innovative product in the Launch stage after the realization of π. We use q_C^π and Π_C^π to denote C's production quantity and profit contingent on the observed value of innovation π. Then, we have

$$\Pi_C^\pi = (\pi + a - q_V - q_C^\pi)q_C^\pi + wq_V. \quad (3.4)$$

By the first order condition, C's best response given q_V is

$$BR_C^\pi(q_V) = (\pi + a - q_V)/2. \quad (3.5)$$

On the other hand, V has to produce facing the uncertainty of innovation. It outputs q_V with respect to the expected value of innovation μ_C, and in response to the expected quantity of C. Its expected profit is

$$\Pi_V^{C\mathrm{NI}} = (\mu_C + a - q_V - \mathbb{E}[BR_C^{\pi}(q_V)])q_V - wq_V. \tag{3.6}$$

Plugging in C's best responses and then optimizing (4.15) with respect to q_V, we obtain

$$q_V = (a + \mu_C - 2w)/2. \tag{3.7}$$

Substituting q_V from (4.16) into C's best responses in (4.14) and then taking expectation, we obtain

$$\mathbb{E}[q_C^{\pi}] = (a + \mu_C + 2w)/4. \tag{3.8}$$

Substituting q_V from (4.16) and $\mathbb{E}[q_C^{\pi}]$ from (4.17), the optimal ex-ante expected profits of V and C are

$$\Pi_V^{C\mathrm{NI}} = (a + \mu_C - 2w)^2/8, \quad \Pi_C^{C\mathrm{NI}} = (a + \mu_C + 2w)^2/16 + \sigma^2/4 + w(a + \mu_C - 2w)/2. \tag{CNI}$$

<u>Outcome SR:</u>

V sources from S, and C produces the regular product in the Sourcing stage prior to the realization of π. V and C's ex-ante expected profits are

$$\Pi_V^{S\mathrm{R}} = (\mu_S + a - q_V - q_C)q_V - wq_V, \quad \Pi_C^{S\mathrm{R}} = (a - q_V - q_C)q_C. \tag{3.9}$$

By the first order condition, (4.18) yields the best responses functions

$$BR_V(q_C) = (\mu_S + a - w - q_C)/2, \quad BR_C(q_V) = (a - q_V)/2. \tag{3.10}$$

Thus, the optimal quantities are

$$q_V = (a + 2\mu_S - 2w)/3, \quad q_C = (a - \mu_S + w)/3. \tag{3.11}$$

Substituting the optimal quantities q_V and q_C from (4.20) into (4.18) yields the optimal ex-ante expected profits as

$$\Pi_V^{S\mathrm{R}} = (a + 2\mu_S - 2w)^2/9, \quad \Pi_C^{S\mathrm{R}} = (a - \mu_S + w)^2/9. \tag{SR}$$

□

Lemma 7. *For technical innovations, suppose V sources from C in the Sourcing stage. Then for any μ_C, μ_S and σ_S^2, there exists Σ^2 such that C postpones the production decision to the Launch stage if and only if $\sigma_C^2 > \Sigma^2$, otherwise C produces the innovative product in the Sourcing stage.*

Proof. Given the ex-ante expected profits in Lemma 6, C would postpone the production decision to the Launch stage if and only if $\Pi_C^{C\mathrm{NI}} > \Pi_C^{C\mathrm{I}}$. One can check that the inequality holds if $\sigma_C^2 > \Sigma^2 = 7(a + \mu_C - 2w)^2/36$; otherwise C produces the innovative product in the Sourcing stage. □

Lemma 6 lists the firms' expected profits in the Sourcing stage which are needed to determine the equilibria of the grand game of sourcing and product choices. Lemma 7 is important because it shows that when the innovation spills over through sourcing, C may voluntarily postpone its production decision and yield market leadership to V if σ_C^2 is sufficiently large. Such behavior is understandable: postponing the production decision allows C to observe the exact value of π and choose a more informed production quantity, and this benefit is more substantial when the prior uncertainty pertaining to π, measured by σ_C^2, is larger. When σ_C^2 is sufficiently large, the benefit outweighs the disadvantage of yielding market leadership to V (choosing a production quantity after V), and C voluntarily postpones its production decision. However, we still need to check whether such cases exist in equilibria, namely whether V would source from C despite innovation spillover.

In practice, innovators indeed source from competitor-suppliers despite innovation spillover. The most prominent recent example is probably Apple and Samsung, with Samsung constantly being sued by Apple for patent infringement while remaining the latter's most important supplier. The common explanation is that Samsung is so much more capable than other suppliers that Apple has no alternatives (Forbes, 2016). Proposition 3 confirms this intuition: when C's capabilities as a supplier are sufficiently better than S, V always sources from C.

Proposition 3. *For technical innovations, if $\mu_C > 2\mu_S$, the grand game's equilibrium outcome is CI or CNI, namely V always sources from C.*

A more interesting question, however, is whether V may ever source from C despite innovation spillover if C offers no advantage over S as a supplier. The next proposition answers this question.

Proposition 4. *For technical innovations, assuming $\mu_C = \mu_S = \mu$ and $\sigma_C^2 = \sigma_S^2 = \sigma^2$, there exist Σ^2 (as in Lemma 7) and M_e such that if $\mu < M_e$ and $\sigma^2 > \Sigma^2$, the grand game's equilibrium outcome is CNI, namely V sources from C, and C produces the innovative product in the Launch stage. Otherwise, the grand game's equilibrium outcome is SR, namely V sources from S, and C produces the regular product in the Sourcing stage.*

Proposition 4 presents a somewhat surprising result: V may willingly source from C despite innovation spillover even when the latter offers no capability advantage over S. With supplier capabilities out of the picture, V's sourcing decision is driven by more subtle strategic considerations. The key observation is that V sources from C only if C would postpone its production decision. Multiple layers of incentives are at work here. When V sources from C, C obtains the innovation through spillover, which seems detrimental for V. However, the spillover also presents C with a tradeoff between competing with V as market co-leaders before learning the exact value of π, and yielding market leadership to V and choosing a more informed production quantity after learning the exact value of π. The latter becomes more attractive to C when the prior uncertainty of the innovation's value, measured by σ_C^2 ($= \sigma^2$ in Proposition 4), is sufficiently large. Anticipating C's concession should innovation spillover occur, V in turn faces a tradeoff between competing with C's regular product head-to-head, and competing with C's innovative product with a head start. It is straightforward to see that the latter becomes more attractive when the prior expectation of the innovation's value, measured by μ_C ($= \mu$ in Proposition 4), is not too large. This insight provides an alternative strategic motivation for why innovators may source from competitor-suppliers despite innovation spillover, aside from simple supplier capability considerations.

It may be tempting to assume that such a strategic motivation is secondary to and dominated by supplier capability considerations, but the next proposition shows that this is not the case, and V may source from C even when C bears a capability disadvantage compared with S.

Proposition 5. *For technical innovations, for any $\mu_C < \mu_S$, there always exist a, w, σ_C^2 and σ_S^2 such that V sources from C in an equilibrium.*

Below we provide a complete description of the equilibrium of the grand game of sourcing and product choices. Note that so far we have always discussed equilibrium *outcomes*, namely what will happen in the equilibrium. A full description of an equilibrium, however, needs to also specify off-equilibrium-path strategies. In our problem, we need to specify C's subsequent actions should V take a different action in the Sourcing stage from the equilibrium. We use the format X/Y to indicate an equilibrium, where X is the equilibrium outcome, and Y is C's action should V deviates from the equilibrium. For example, equilibrium SR/NI means that in the equilibrium V sources from S and C produces the regular product in the Sourcing stage, but if V were to source C then C would produce the innovative product in the Launch stage. Recall that $\alpha \doteq \mu_C/\mu_S$.

Proposition 6. *For technical innovations, there exist $F_\alpha \in (1, 2)$, M, and Σ^2 (as in Lemma 7) such that the equilibrium is*

1. *CI/R, if $\sigma_C^2 < \Sigma^2$ and $\alpha > 2$;*

2. *SR/I, if $\sigma_C^2 < \Sigma^2$ and $\alpha < 2$;*

3. *CNI/R, if $\sigma_C^2 > \Sigma^2$, and $\alpha > F_\alpha$ or $\mu_C < M$;*

4. *SR/NI, if $\sigma_C^2 > \Sigma^2$, $\mu_C > M$ and $\alpha < F_\alpha$.*

Proof. We show Proposition 6 as it provides the complete characterization of the equilibria, and then Proposition 3, 4 and 5 follow.

CI/R is the equilibrium if and only if $\Pi_C^{C\text{I}} > \Pi_C^{C\text{NI}}$ and $\Pi_V^{C\text{I}} > \Pi_V^{S\text{R}}$. SR/I is the equilibrium if and only if $\Pi_C^{C\text{I}} > \Pi_C^{C\text{NI}}$ and $\Pi_V^{S\text{R}} > \Pi_V^{C\text{I}}$. CNI/R is the equilibrium if and only if $\Pi_C^{C\text{NI}} > \Pi_C^{C\text{I}}$ and $\Pi_V^{C\text{NI}} > \Pi_V^{S\text{R}}$. SR/NI is the equilibrium if and only if $\pi_C^{C\text{NI}} > \Pi_C^{C\text{I}}$ and $\Pi_V^{S\text{R}} > \Pi_V^{C\text{NI}}$. One can check these inequalities hold respectively under the conditions in 1, 2, 3 and 4 in Proposition 6, where $F_\alpha = 4(a+2w)[(8+9\sqrt{2})a - 2(8+3\sqrt{2})w]/(49a^2+20aw-92w^2)$, $M = \alpha(a-2w)[6\sqrt{2}(-32+9\alpha^2)|\alpha - 2| + (16-9\alpha)|32-9\alpha^2|]/[(-32+9\alpha^2)|32-9\alpha^2|]$ and $\Sigma^2 = 7(a+\mu_C-2w)^2/36$.

Thus, one can see that the equilibrium is either CI or CNI if $\alpha > 2$ (Proposition 3); that assuming $\mu_C = \mu_S = \mu$ and $\sigma_C^2 = \sigma_S^2 = \sigma^2$, the equilibrium is CNI if $\mu < M_e = (6\sqrt{2}-7)(a-2w)/23$ and $\sigma^2 > \Sigma^2$ (Proposition 4); that for any $\alpha < 1$, there exist a, w, σ_C^2 and σ_S^2 such that CNI is the equilibrium (Proposition 5). □

To summarize, for technical innovations, an innovator may willingly source from a competitor-supplier despite innovation spillover for two different reasons. The first is the straightforward supplier capability consideration: when the competitor-supplier is much more capable than alternative suppliers, the innovator will source from the competitor-supplier. The second is a more subtle strategic motivation: the innovator may source from the competitor-supplier if it anticipates that the latter would postpone production of the innovative product until learning how the innovation is received by consumers. In other words, an innovator may willingly allow innovation spillover to a competitor-supplier *in exchange for market leadership.* The strategic motivation alone can drive an innovator to source from a competitor-supplier, even when the latter has inferior capability compared with non-competitor suppliers.

3.4.2 Non-technical innovations

Recall that in the simplified non-technical innovation model, π has mean μ and variance σ^2 regardless of the supplier, $\pi_+ \doteq \max\{\pi, 0\}$ and its mean and variance are μ_+ and σ_+^2, and $\Delta\mu \doteq \mu_+ - \mu$ captures the value of learning π before the production decision. In order to present the expected profits in the Sourcing stage, we need to introduce a new notation. Note that for non-technical innovations, whenever C postpones production, its subsequent decision will be contingent on the realized value of π and is uncertain in the Sourcing stage. In these cases we combine the possible decisions in parentheses. For example, scenario CN(IR) refers to the scenario where in the Sourcing stage V sources from C which will postpone the production decision until the Launch stage when it may produce either the regular or the innovative product.

Lemma 8. *For non-technical innovations, the Sourcing-stage expected equilibrium profits of the production game for all relevant scenarios are*

$$\Pi_V^{CI} = (a + \mu - 2w)^2/9, \quad \Pi_C^{CI} = (a + \mu + w)^2/9 + w(a + \mu - 2w)/3,$$

$$\Pi_V^{CN(IR)} = (a + 2\mu - \mu_+ - 2w)^2/8, \quad \Pi_C^{CN(IR)} = (a - 2\mu + 3\mu_+ + 2w)^2/16,$$

$$\Pi_V^{SN(IR)} = (a + 2\mu - \mu_+ - 2w)^2/8, \quad \Pi_C^{SN(IR)} = (a - 2\mu + 3\mu_+ + 2w)^2/16 + \sigma_+^2/4.$$

Under assumption $\mu > (a - 2w)/7$, scenario SR is dominated ($\Pi_C^{SR} < \Pi_C^{SN(IR)}$) and thus its expected profits are omitted.

Proof. We derive the ex-ante expected profits of V and C in outcome CI, CN(IR) and SN(IR).

Outcome CI:

V sources from C, and C produces the innovative product in the Sourcing stage before the realization of π. The ex-ante expected profits are derived simply by replacing μ_C with μ in Π_V^{CI} and Π_C^{CI} in Lemma 6:

$$\Pi_V^{C\mathrm{I}} = (a + \mu - 2w)^2/9, \quad \Pi_C^{C\mathrm{I}} = (a + \mu + w)^2/9 + w(a + \mu - 2w)/3. \qquad (C\mathrm{I})$$

Outcome CN(IR):

V sources from C, and C produces either the innovative product or the regular product in the Launch stage after the realization π. We use $q_C^{\pi_+}$ and $\Pi_C^{\pi_+}$ to denote C's production quantity and profit contingent on the observed value of innovation π. Then, we have

$$\Pi_C^{\pi_+} = (\pi_+ + a - q_V - q_C^{\pi_+})q_C^{\pi_+} + wq_V. \qquad (3.12)$$

By the first order condition, C's best response given q_V is

$$BR_C^{\pi_+}(q_V) = (\pi_+ + a - q_V)/2. \qquad (3.13)$$

On the other hand, V has to produce facing the uncertainty of innovation. It chooses q_V with respect to the expected value of innovation μ_C, and in response to the expected quantity of C. Its expected profit is

$$\Pi_V^{C\mathrm{NI}} = (\mu + a - q_V - \mathbb{E}[BR_C^{\pi_+}(q_V)])q_V - wq_V. \qquad (3.14)$$

Plugging in C's best responses and then optimizing (3.14) with respect to q_V, we obtain

$$q_V = (a + 2\mu - \mu_+ - 2w)/2. \qquad (3.15)$$

Substituting q_V from (3.15) into C's best responses in (3.13) and then taking expectation, we obtain

$$\mathbb{E}[q_C^{\pi_+}] = (a - 2\mu + 3\mu_+ + 2w)/4. \tag{3.16}$$

Substituting q_V from (3.15) and $\mathbb{E}[q_C^{\pi_+}]$ from (3.16) into (4.21) and (3.14) yields the optimal ex-ante expected profits of V and C as

$$\Pi_V^{C\text{N(IR)}} = (a + 2\mu - \mu_+ - 2w)^2/8, \quad \Pi_C^{C\text{N(IR)}} = (a - 2\mu + 3\mu_+ + 2w)^2/16. \tag{CN(IR)}$$

Outcome SN(IR):

V sources from S, and C produces the C produces either the innovative product or the regular product in the Launch stage after the realization π. The ex-ante expected profits are the same as in outcome CN(IR), except that C receives no profit from producing for V:

$$\Pi_V^{S\text{N(IR)}} = (a + 2\mu - \mu_+ - 2w)^2/8, \quad \Pi_C^{S\text{N(IR)}} = (a - 2\mu + 3\mu_+ + 2w)^2/16 + \sigma_+^2/4. \tag{SN(IR)}$$

To see why $\mu > (a - 2w)/7$ leads to scenario SR being dominated ($\Pi_C^{S\text{R}} < \Pi_C^{S\text{N(IR)}}$), substituting μ_S with μ in $\Pi_C^{S\text{R}}$ in Lemma 6 yields $\Pi_C^{S\text{R}} = (a - \mu + w)^2/9$. One can confirm that $\Pi_C^{S\text{R}} > \Pi_V^{S\text{N(IR)}}$ if and only if $\mu < (a - 2w)/7$, $\Delta\mu < 1/9(a - 7\mu - 2w)$ and $\sigma_+^2 < 1/36(7a^2 - 54a\Delta\mu - 81\Delta\mu^2 - 50a\mu - 54\Delta\mu\ \mu + 7\mu^2 - 4aw - 108\Delta\mu w - 68\mu w - 20w^2)$. Therefore, $\mu > (a - 2w)/7$ ensures that $\Pi_C^{S\text{R}} < \Pi_V^{S\text{N(IR)}}$ for any $\Delta\mu$ and σ_+^2. □

Lemma 9. *For non-technical innovations, suppose V sources from C in the Sourcing stage. Then for any μ, there exist D_C and Σ_+^2 such that C immediately produces the innovative product if and only if $\Delta\mu < D_C$ and $\sigma_+^2 < \Sigma_+^2$, otherwise C postpones the production decision to the Launch stage.*

Proof. Given the ex-ante expected profits in Lemma 8, C would produce the innovative product in the Sourcing stage if and only if $\Pi_C^{CI} > \Pi_C^{CN(IR)}$. One can check that the inequality holds if and only if $\Delta\mu < D_C = [-3a - 3\mu - 2w + 4\sqrt{a^2 + 2a\mu + \mu^2 - aw - \mu w + 2w^2}]/9$ and $\sigma_+^2 < \Sigma_+^2 = [7a^2 - 81\Delta\mu^2 + 7(\mu - 2w)^2 - 18\Delta\mu(3\mu + 2w) - 2a(27\Delta\mu - 7\mu + 14w)]/36$; otherwise, C would produce either the innovative product or the regular product in the Launch stage. □

Lemma 8 lists the firms' expected profits in the Sourcing stage which are needed to determine the equilibria of the grand game of sourcing and product choices. Lemma 9 states that if the innovation spills over through sourcing, C would immediately take advantage of it and produce the innovative product if postponing production to learn the innovation's exact value and then contingently choosing the product and its production quantity does not generate much benefit, where $\Delta\mu$ and σ_+^2 reflectively capture the benefits from contingently choosing the product and its production quantity (which we will explain in more detail later). Once again, we still need to check whether such cases exist in equilibria, namely whether V would source from C despite innovation spillover through sourcing. The answer is provided in the next proposition and illustrated in Figure 3.3.

Proposition 7. *For non-technical innovations, there exist $D_V < D_C$ (as in Lemma 9) and Σ_+^2 (as in Lemma 9) such that the grand game's equilibrium is*

1. *CN(IR)/N(IR) or SN(IR)/N(IR), if $\Delta\mu > D_C$ or $\sigma_+^2 > \Sigma_+^2$;*
2. *SN(IR)/I, if $\Delta\mu < D_V$ and $\sigma_+^2 < \Sigma_+^2$;*
3. *CI/N(IR), if $D_V < \Delta\mu < D_C$ and $\sigma_+^2 < \Sigma_+^2$.*

Proof. CN(IR)/N(IR) or SN(IR)/N(IR) is the equilibrium if and only if $\pi_C^{\mathrm{CN(IR)}} > \Pi_C^{\mathrm{CI}}$. SN(IR)/I is the equilibrium if and only if $\Pi_C^{\mathrm{CI}} > \Pi_C^{\mathrm{CN(IR)}}$ and $\Pi_V^{\mathrm{SN(IR)}} > \Pi_V^{\mathrm{CI}}$.

CI/N(IR) is the equilibrium if and only if $\Pi_C^{CI} > \Pi_C^{CN(\mathrm{IR})}$ and $\Pi_V^{CI} > \Pi_V^{SN(\mathrm{IR})}$. One can check these inequalities hold respectively under the conditions in 1, 2, and 3, where $D_V = (2\sqrt{2}-3)(a+\mu-2w)/3$, $D_C = [-3a-3\mu-2w+4\sqrt{a^2+2a\mu+\mu^2-aw-\mu w+2w^2}]/9$, and $\Sigma_+^2 = [7a^2-81\Delta\mu^2+7(\mu-2w)^2-18\Delta\mu(3\mu+2w)-2a(27\Delta\mu-7\mu+14w)]/36$. □

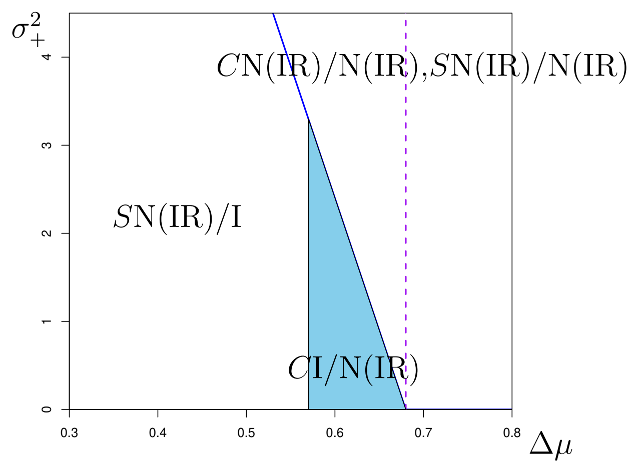

FIGURE 3.3: Equilibrium regions for non-technical innovations ($a = 10$, $w = 3$, $\mu = 6$)

Proposition 7 characterizes three equilibrium cases based on two parameters: $\Delta\mu \doteq \mu_+ - \mu$ and σ_+^2, where $\Delta\mu$ measures the benefit of C contingently choosing a product upon learning the exact value of π, and σ_+^2 measures the benefit of a firm contingently choosing a production quantity (after choosing the product) upon learning the value of π. One can see that these two parameters capture two layers of benefits of C postponing production to the Launch stage. Proposition 7 states that when either benefit is sufficiently large, C will never produce in the Sourcing stage regardless of V's sourcing decision, and V is indifferent between sourcing from C and S (Case 1). On the other hand, when both benefits are sufficiently small, V prefers to source from S and let C postpone production to the Launch stage to enjoy market leadership while not foregoing much advantage to C (Case 2).

The most interesting equilibrium, however, is found in Case 3. In this case, σ_+^2 is sufficiently small and the result is largely driven by $\Delta\mu$ which takes moderate values. In this range, $\Delta\mu$ is sufficiently large that the advantage granted to C postponing production to the Launch stage is significant enough that V prefers C to produce in the Sourcing stage. On the other hand, $\Delta\mu$ is sufficiently small that C is willing to forgo the benefits of producing in the Launch stage if it could produce the innovative product in the Sourcing stage as a market co-leader alongside V. Accordingly, the resulting equilibrium is one where V sources from C and allows innovation spillover to induce C to produce the innovative product in the Sourcing stage, achieving both firms' preferred outcome.

Therefore, for non-technical innovations, we also find a strategic motivation for why innovators may source from competitor-suppliers despite innovation spillover. Once again, multiple layers of incentives are at work here. For design-driven non-technical innovations, a competitor-supplier can always learn about the innovation after the product launch. When the innovator sources from the competitor-supplier, the latter obtains early access to the innovation and may compete with the innovator head-to-head; otherwise the competitor-supplier has to wait until after the innovative product is revealed to public, giving the innovator a head start. In this aspect, sourcing from a competitor-supplier is detrimental to the innovator. However, when a competitor-supplier learns about an innovation after its launch, it also learns about its reception and will only imitate a well-received innovation. This puts the innovator, which is committed to the innovative product before its launch and bears the risk of it being unpopular, at a significant disadvantage. Therefore, if the competitor-supplier would immediately imitate the innovation when spillover occurs, the benefit of the innovator sourcing from the competitor-supplier and inducing it to imitate the innovation before knowing its reception may outweigh the aforementioned disadvantage of losing the head start. In summary, for non-technical innovations, an innovator may strategically source from a competitor-supplier and allow innovation spillover through sourcing *in exchange for the latter to share innovation risks.*

3.4.3 Comparison of technical and non-technical innovations

In our analyses of both technical and non-technical innovations, we have found that an innovator may strategically source from a competitor-supplier despite innovation spillover, when the latter offers no direct advantage over non-competitor suppliers. However, the motivations for technical and non-technical innovations are polar opposites. For technical innovations, an innovator may source from a competitor-supplier so that the latter would *postpone* its production quantity decision and yield market leadership to the former. By contrast, for non-technical innovations, an innovator may source from a competitor-supplier so that the latter would *immediately* produce the innovative product and become market co-leaders alongside the former. However, these insights do not contradict each other. They are directly driven by the key difference between technical and non-technical innovations that the former can only spill over through sourcing, whereas the latter can spill over through sourcing as well as in the market.

For technical innovations that can only spill over through sourcing, an innovator has the ability to outright prevent spillover to a competitor-supplier by not sourcing from it. As such, the innovator needs to choose between having no competing innovative product and being the market leader against a competing innovative product, and our strategic motivation is justified when the latter prevails.

For non-technical innovations, since the innovation will eventually spill over in the market to the competitor-supplier if not earlier through sourcing, an innovator cannot outright prevent spillover but can only influence its timing. Also, the innovator carries a significant disadvantage if the competitor-supplier postpones production until after learning the innovation's reception, because the latter will only imitate a well-received innovation while the former bears the entire risk of an unpopular innovation. Therefore, the innovator can choose between co-leading the market and sharing innovation risks with a competitor, and leading the market against a competitor which only reaps benefits but does not bear risks of the innovation, and our strategic motivation is justified when the former prevails.

3.5 Extensions

We have so far analyzed simplified models and driven clear insights about managing technical and non-technical innovation spillover in sourcing. In this section, we first verify that the most interesting results that drive our main insights remain valid without the simplifications, and then consider a more complex market model with partial substitution between regular and innovative products and once again recover the most interesting results, thus confirming the robustness of our main insights.

3.5.1 Technical innovations of possibly negative values

In this extension, we allow a technical innovation's value π to take negative values. For tractability we focus on the case where C and S have the same capabilities as in Proposition 4. Since π can be negative, we define π_+ as in Section 3.4.2. We show that the equilibrium in Proposition 4 is recovered in this model and illustrate it in Figure 3.4.

Proposition 8. *For technical innovations of possibly negative values, assuming $\mu_C = \mu_S = \mu$ and $\sigma_C^2 = \sigma_S^2 = \sigma^2$, there exist D_+, M_e (as in Proposition 4) and Σ_+^2 (as in Lemma 9) such that if $\mu_C < M_e$, $\Delta\mu < D_+$ and $\sigma_+^2 > \Sigma_+^2$, the grand game's equilibrium outcome is $CN(IR)$, namely V sources from C, and C produces the innovative or the regular product in the Launch stage depending on whether its value is positive or negative.*

Proof. Under this formulation, there are four possible outcomes, namely, CI, CN(IR), SR and SNR. The equilibrium expected profits for the possible outcomes are:

$$\Pi_V^{CI} = (a + \mu_C - 2w)^2/9, \quad \Pi_C^{CI} = (a + \mu_C + w)^2/9 + w(a + \mu_C - 2w)/3, \qquad (C\text{I})$$

$$\Pi_V^{CN(IR)} = (a+\mu_C-2w)^2/8, \quad \Pi_C^{CN(IR)} = (a+\mu_C+2w)^2/16+\sigma_C^2/4+w(a+\mu_C-2w)/2, \qquad (C\text{N(IR)})$$

$$\Pi_V^{SR} = (a + 3\mu_S - 2w)^2/9, \quad \Pi_C^{SR} = (a - 3\mu_S + w)^2/9, \qquad (S\text{R})$$

and

$$\Pi_V^{SNR} = (a + 3\mu_S - 2w)^2/8, \quad \Pi_C^{SNR} = (a - 5\mu_S + 2w)^2/16 + \sigma_S^2/4. \qquad (S\text{NR})$$

CN(IR) is the equilibrium outcome if and only if $\Pi_C^{CN(IR)} > \Pi_C^{CI}$, $\Pi_C^{SR} > \Pi_C^{SNR}$ and $\Pi_V^{CN(IR)} > \Pi_V^{SR}$. When $\mu_S = \mu_C$, one can check that those inequalities hold under the conditions in Proposition 8, where $M^* = (4\sqrt{2} - 5)(a - 2w)/21$, $\Sigma^2 = 7(a + \mu_C - 2w)^2/36$ and $\Sigma^{2\Sigma^2 *} = (7a^2 - 6a\mu_C - 81\mu_C^2 - 4aw + 84\mu_C w - 20w^2)/36$. □

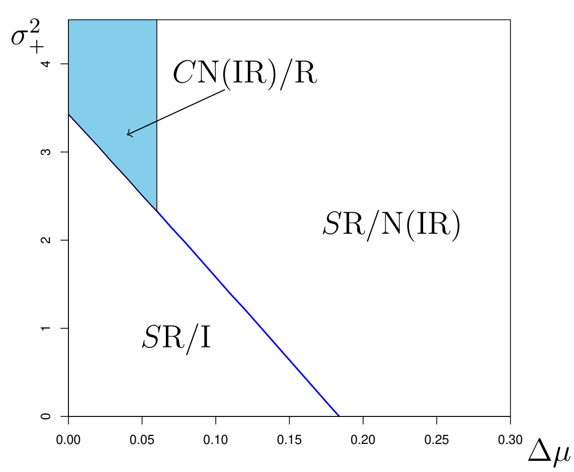

FIGURE 3.4: technical innovation (possibly negative value) equilibrium regions ($a = 10$, $w = 3$, $\mu_C = 0.2$)

The proposition shows that our key insight for technical innovations is preserved. The innovator may strategically source from a competitor-supplier if doing so induces the latter to postpone production and yield market leadership to the former. Although in this extension the innovation's value can be negative and thus the competitor-supplier postponing production to the Launch stage enjoys a larger benefit by avoiding imitating an unpopular innovation, the innovator's first-mover advantage may still be enough to justify strategically sourcing from the competitor-supplier.

3.5.2 Non-technical innovations under different supplier capabilities

In this extension, we consider a non-technical innovation satisfying other definitions in Section 3.2 but allow different supplier capabilities (i.e., sourcing from $C(S)$ leads to value of innovation $\pi_{C(S)}$ with mean $\mu_{C(S)}$ and variance $\sigma^2_{C(S)}$). For tractability we normalize the market size to $a = 1$. Let $\pi_{C(S)+} \doteq \max\{\pi_{C(S)}, 0\}$ with mean $\mu_{C(S)+}$ and variance $\sigma^2_{C(S)+}$. Let $\Delta\mu_{C(S)} \doteq \mu_{C(S)+} - \mu_{C(S)}$.

Proposition 9. *For non-technical innovations under different supplier capabilities, assuming $a = 1$, $\mu_S > \mu_C (> (a-2w)/7)$, $\Delta\mu_S < \Delta\mu_C$, and $\sigma^2_{C+} = \sigma^2_{S+} \doteq \tilde{\sigma}^2_+$, there exist $\underline{\Delta}_S$, $\overline{\Delta}_C$, $\overline{\mu}_S$, $\underline{\mu}_C$, and $\tilde{\Sigma}^2_+$ such that the grand game's equilibrium is CI/N(IR) if $\underline{\mu}_C < \mu_C < \mu_S < \overline{\mu}_S$, $\underline{\Delta}_S < \Delta\mu_S < \Delta\mu_C < \overline{\Delta}_C$, and $\tilde{\sigma}^2_+ < \tilde{\Sigma}^2_+$.*

Proof. The ex-anti expected profits for the possible outcomes are:

$$\Pi_V^{CI} = (a + \mu_C - 2w)^2/9, \quad \Pi_C^{CI} = (a + \mu_C + w)^2/9 + w(a + \mu_C - 2w)/3, \tag{CI}$$

$$\Pi_V^{CN(IR)} = (a + \mu_C - \Delta\mu_C - 2w)^2/8, \Pi_C^{CN(IR)} = (a + \mu_C + 3\Delta\mu_C + 2w)^2/16, \tag{CN(IR)}$$

and

$$\Pi_V^{SN(IR)} = (a + \mu_S - \Delta\mu_S - 2w)^2/8, \quad \Pi_C^{SN(IR)} = (a + \mu_S + 3\Delta\mu_S + 2w)^2/16 + \tilde{\sigma}^2_+/4. \tag{SN(IR)}$$

CI/N(IR) is the equilibrium if and only if $\Pi_C^{CI} > \Pi_C^{C\mathrm{N(IR)}}$ and $\Pi_V^{CI} > \Pi_V^{S\mathrm{N(IR)}}$. When $a = 1$, one can check that there exist $\underline{\Delta}_S$, $\overline{\Delta}_C$, $\overline{\mu}_S$, $\underline{\mu}_C$, and $\tilde{\Sigma}_+^2$ such that the two inequalities hold under the conditions in the proposition. □

This proposition recovers the most interesting equilibrium for non-technical innovations in the base model (Proposition 7's equilibrium 3) that the innovator strategically sources from C despite innovation spillover, even when C bears a capability disadvantage compared with S. It shows that the insight behind the observation of Proposition 7's equilibrium 3 is robust. The equilibrium conditions mostly resemble those for the latter; an additional condition guarantees that the capability difference between S and C ($\mu_S - \mu_C$) is not too large.

3.5.3 Imperfect substitution between regular and innovative products

In the base model we have assumed perfect substitution between regular and innovative products because the focus of our research is on the sourcing side rather than the market side, although one may argue for imperfect substitution between the two given the differentiation. As an extension we consider the following market model. Recall that V always outputs the innovative product. If C also outputs the innovative product, the market price is $a + \pi - q_V - q_C$ for both firms (the same as the base model). If C outputs the regular product, the market price of V's product is $a + \pi - q_V - \gamma q_C$, and the market price of C's product is $a - q_C - \gamma q_V$, where $\gamma \in [0, 1]$ indicates the substitutability between regular and innovative products. The resulting model is significantly complicated. For tractability, we adopt a two-point demand distribution (the base model assumes a general demand distribution), assume equal capabilities of C and S, and present all results assuming market size $a = 1$ and sourcing price $w = 0.1$ (similar results can be observed for other values of a and w). First, consider technical innovations. We assume that $\pi = \pi_0 > 0$ with probability p, and $\pi = 0$ with probability $1 - p$. The following proposition recovers the most interesting equilibrium for technical innovations in the base model (Proposition 4 and Proposition 6's equilibrium 3) when the regular and innovative products' substitutability is not too low.

Proposition 10. *For technical innovations, there exist R_1, P_1, Π_1 and Π_2 such that the grand game's equilibrium is CN(IR)/R if $R_1 < \gamma \leqslant 1$, $p < P_1$ and $\Pi_1 < \pi_0 < \Pi_2$.*

Proof. First note that with product differentiation, we have CN(IR) instead of CNI, and CR is no longer dominated. The ex-ante expected profits for the possible outcomes are:

$$\Pi_V^{CI} = (a + p\pi_0 - 2w)^2/9, \quad \Pi_C^{CI} = (a^2 + 2ap\pi_0 + p^2\pi_0^2 + 5aw + 5p\pi_0 w - 5w^2)/9, \quad (C\text{I})$$

$$\Pi_V^{C\text{N(IR)}} = (p\pi_0 + a(2 + p(\gamma - 1) - \gamma) - 2w)^2/(8(2 - \gamma^2 + p(\gamma^2 - 1))),$$

$$\begin{aligned}\Pi_C^{C\text{N(IR)}} = {} & (p^3\pi_0^2(9 - 13\gamma^2 + 4\gamma^4) + a^2(3p^3(-1 + \gamma)^3(1 + \gamma) + (-4 + 2\gamma + \gamma^2)^2 - \\ & p^2(-1 + \gamma)^2(-16 - 6\gamma + 5\gamma^2) \\ & + p(-28 + 36\gamma + 5\gamma^2 - 14\gamma^3 + \gamma^4)) + 4(-8 + 5\gamma^2)w^2 + p^2\pi_0(\pi_0(-24 + 29\gamma^2 - 8\gamma^4) + 20(-1 + \gamma^2)w) \\ & + 4p(\pi_0^2(-2 + \gamma^2)^2 + \pi_0(8 - 5\gamma^2)w - 5(-1 + \gamma^2)w^2) + 2a(p^3\pi_0(-1 + \gamma)^2(3 + 7\gamma + 4\gamma^2) \\ & + 2(8 - 6\gamma^2 + \gamma^3)w - p^2(-1 + \gamma)(\pi_0(-10 - 11\gamma + 6\gamma^2 + 8\gamma^3) - 2(-1 + \gamma^2)w) \\ & + p(\pi_0(8 - 10\gamma^2 - \gamma^3 + 4\gamma^4) + 2(-6 + \gamma + 7\gamma^2 - 2\gamma^3)w)))/(16(2 - \gamma^2 + p(-1 + \gamma^2))^2), \\ & \qquad (C\text{N(IR)})\end{aligned}$$

$$\Pi_V^{C\text{R}} = (2p\pi_0 + a(2 - \gamma) - 2w)^2/(4 - \gamma^2)^2,$$

$$\begin{aligned}\Pi_C^{C\text{R}} = {} & 1/(4 - \gamma^2)^2(a^2(\gamma - 2)^2 + p^2\pi^2\gamma^2 - 4p\pi_0(\gamma^2 - 2)w + (3\gamma^2 - 8)w^2 \\ & + a(\gamma - 2)(2p\pi_0\gamma + (-4 - 2\gamma + \gamma^2)w)), \quad (C\text{R})\end{aligned}$$

$$\Pi_V^{S\text{R}} = (2p\pi_0 + a(\gamma - 2) - 2w)^2/(4 - \gamma^2)^2, \quad \Pi_C^{S\text{R}} = (\gamma(p\pi_0 - w) - (2 - \gamma)a)^2/(4 - \gamma^2)^2. \quad (S\text{R})$$

CN(IR)/R is the equilibrium if and only if $\Pi_C^{CN(IR)} > \Pi_C^{CI}$, $\Pi_C^{CN(IR)} > \Pi_C^{CR}$ and $\Pi_V^{CN(IR)} > \Pi_V^{SR}$. When $a = 1$ and $w = 1/10$, one can confirm that there exist R_1, P_1, Π_1 and Π_2 such that the inequalities hold under the conditions in the proposition. □

For non-technical innovations, we assume that $\pi = \pi_0 = 0.5$ with probability p, and $\pi = -\pi_0 = -0.5$ with probability $1-p$. To ensure $\mathbb{E}(\pi) > 0$, we assume $p > 0.5$. The following proposition recovers the most interesting equilibrium for non-technical innovations in the base model (Proposition 7's equilibrium 3) when the regular and innovative products' substitutability is not too low.

Proposition 11. *For non-technical innovations, there exist R_2, $P_2 > 0.5$, and P_3 such that the grand game's equilibrium is CI/N(IR) if $R_2 < \gamma \leqslant 1$ and $P_2 < p < P_3$.*

Proof. First note that with product differentiation, we have CN(IR) instead of CNI, and CR is no longer dominated. The ex-anti expected profits for the possible outcomes are:

$$\Pi_V^{\text{CI}} = (a + p\pi_0 - (1-p)\pi_0 - 2w)^2/9, \Pi_C^{\text{CI}} = (a + p\pi_0 - (1-p)\pi_0 + w)^2/9, \quad (C\text{I})$$

$$\Pi_V^{C\text{N(IR)}} = ((-2+3p)\pi_0 + a(2 + p(-1+\gamma) - \gamma) - 2w)^2/(8(2 - \gamma^2 + p(-1+\gamma^2))),$$

$$\begin{aligned}\Pi_C^{C\text{N(IR)}} = {} & (p^3\pi_0^2(25 - 29\gamma^2 + 4\gamma^4) + a^2(3p^3(-1+\gamma)^3(1+\gamma) + (-4 + 2\gamma + \gamma^2)^2 \\ & -p^2(-1+\gamma)^2(-16-6\gamma+5\gamma^2)+p(-28+36\gamma+5\gamma^2-14\gamma^3+\gamma^4))+p^2\pi_0(\pi_0(-60+65\gamma^2-8\gamma^4) \\ & + 44(-1+\gamma^2)w) + 4p(\pi_0^2(9 - 10\gamma^2 + \gamma^4) + \pi_0(22 - 17\gamma^2)w \\ & - 5(-1+\gamma^2)w^2) + 4(\pi_0^2\gamma^2 + 2\pi_0(-4 + 3\gamma^2)w \\ & +(-8+5\gamma^2)w^2)+2a(p^3\pi_0(-1+\gamma)^2(5+9\gamma+4\gamma^2)-p^2(-1+\gamma)(\pi_0(-16-5\gamma+12\gamma^2+8\gamma^3) \\ & - 2(-1+\gamma^2)w) + p(\pi_0(12 - 18\gamma - 4\gamma^2 + 5\gamma^3 + 4\gamma^4) + 2(-6 + \gamma + 7\gamma^2 - 2\gamma^3)w) \\ & + 2(-\pi_0\gamma(-4 + 2\gamma + \gamma^2) + (8 - 6\gamma^2 + \gamma^3)w)))/(16(2 - \gamma^2 + p(-1+\gamma^2))^2), \quad (C\text{N(IR)})\end{aligned}$$

$$\Pi_V^{C\mathrm{R}} = (a(-2+\gamma) + 2(\pi_0 - 2p\pi_0 + w))^2/(-4+\gamma^2)^2,$$

$$\Pi_C^{C\mathrm{R}} = 1/(-4+\gamma^2)^2(a^2(-2+\gamma)^2 + (1-2p)^2\pi_0^2\gamma^2 - 4(-1+2p)\pi_0(-2+\gamma^2)w + (-8+3\gamma^2)w^2 + a(-2+\gamma)(2(-1+2p)\pi_0\gamma + (-4-2\gamma+\gamma^2)w)), \quad (C\mathrm{R})$$

$$\Pi_V^{S\mathrm{R}} = (a(-2+\gamma) + 2(\pi_0 - 2p\pi_0 + w))^2/(-4+\gamma^2)^2, \Pi_C^{S\mathrm{R}} = (a(-2+\gamma). \qquad (S\mathrm{R})$$

$$\Pi_V^{S\mathrm{N(IR)}} = ((-2+3p)\pi_0 + a(2+p(-1+\gamma)-\gamma) - 2w)^2/(8(2-\gamma^2+p(-1+\gamma^2))),$$

$$\Pi_C^{S\mathrm{N(IR)}} = (p^3\pi_0^2(9-13\gamma^2+4\gamma^4) + a^2(3p^3(-1+\gamma)^3(1+\gamma) + (-4+2\gamma+\gamma^2)^2 - p^2(-1+\gamma)^2(-16-6\gamma+5\gamma^2) + p(-28+36\gamma+5\gamma^2-14\gamma^3+\gamma^4)) + 4\gamma^2w^2 + p^2\pi_0(\pi_0(-24+29\gamma^2-8\gamma^4) + 12(-1+\gamma^2)w) + 4p(\pi_0^2(-2+\gamma^2)^2 + \pi_0(4-3\gamma^2)w - (-1+\gamma^2)w^2) + 2a(p^3\pi_0(-1+\gamma)^2(3+7\gamma+4\gamma^2) - 2\gamma(-4+2\gamma+\gamma^2)w - p^2(-1+\gamma)(\pi_0(-10-11\gamma+6\gamma^2+8\gamma^3) + 2(-1+\gamma^2)w) + p(\pi_0(8-10\gamma^2-\gamma^3+4\gamma^4) + 2(2-5\gamma+\gamma^2+2\gamma^3)w)))/(16(2-\gamma^2+p(-1+\gamma^2))^2), \quad (S\mathrm{N(IR)})$$

CI/N(IR) is the equilibrium if and only if $\Pi_C^{C\mathrm{I}} > \Pi_C^{C\mathrm{N(IR)}}$, $\Pi_C^{C\mathrm{I}} > \Pi_C^{C\mathrm{R}}$, $\Pi_C^{S\mathrm{N(IR)}} > \Pi_C^{S\mathrm{R}}$, and $\Pi_V^{C\mathrm{I}} > \Pi_V^{S\mathrm{N(IR)}}$. When $a = 1$, $w = 1/10$ and $\pi_0 = 1/2$, one can confirm that there exist R_2, P_2, and P_3 such that the inequalities hold under the conditions in the proposition. □

Intuitively, imperfect substitution provides an incentive for C to produce the regular product by dampening its competition with V's innovative product. It means that C is less likely to produce the innovative product even if V sources from C, which weakens V's motivation to strategically source from C and enable the latter to produce the innovative product (as discussed in Section 3.4.3). Despite this effect, we find that these insights are robust enough that V may still strategically source from C under imperfect substitution as long as the substitutability is not too low.

3.6 Concluding remarks

This chapter explores an innovator's sourcing decisions for an innovative product between a competitor-supplier and a non-competitor supplier in the presence of innovation spillover. Distinct from existing research on spillover of technologies which carry known values, we emphasize the ex-ante uncertain values of innovations. We further distinguish technical and non-technical innovations; the former heavily involve suppliers during development and can only spill over through sourcing, whereas the latter are primarily driven by designs and can spill over through sourcing as well as in the market. The combination of ex-ante uncertain values, production timing, and two types of innovations offers a very rich setting for the innovator's sourcing decisions.

Through analysis we find that for both types of innovations, the innovator may strategically source from the competitor-supplier; more interestingly, the strategic motivations of sourcing from the competitor-supplier are polar opposites for technical and non-technical innovations. For technical innovations, the innovator may source from the competitor-supplier so that the latter would postpone launching the innovative product; and for non-technical innovations the innovator may source from the competitor-supplier so that the latter would immediately launch the innovative product alongside the innovator. The apparently contradicting insights are driven by the key difference between the two types of innovations, and can potentially inform strategic sourcing decisions under innovation spillover risks. Extensions confirm the robustness of these insights.

In this chapter we focus our study on a single product cycle. A promising future research direction to follow this work is repeated sourcing decisions. When an innovator iteratively improves its product in multiple generations and sources repeatedly from a supplier, strategies unavailable for one-time sourcing decisions may be employed to effectively manage spillover. While the required analysis is far beyond the scope of this chapter, the insights of the non-repeated model would serve as a foundation for understanding the repeated problem.

4

Technology Adoption and Information Acquisition in a Partnership

4.1 Introduction

A tradeoff inherent to managerial decision-making under uncertainty is that of committing to a decision with an uncertain outcome vs. delaying the decision in hope of reducing the uncertainty (at the cost of acquiring information and/or expertise, as well as cost of delay). For example, managing a project or developing a product with an uncertain market value (with the decision to launch the product or to abandon the project) or considering adoption of a new technology whose benefit is uncertain (with the decision to either adopt or reject the new technology), can be cast as such decision-making problems.

This generic problem has been well-studied in the decision analysis literature in the context of optimal information acquisition for technology adoption (starting with the classical model of McCardle, 1985, and many papers that followed it; some of which are discussed in Section 4.1.1). A critical modeling assumption in this literature is that each decision is made by a single decision-maker, which allows for establishing optimal policies by analyzing a single optimization problem (i.e., maximizing expected utility of the decision-maker). Many business settings, however, require joint decision-making among business partners whose objectives might not be identical. For example, a startup developing a new product is often financed by venture capital. While startup has the expertise to develop the product, those providing capital might not be willing to do so indefinitely. Similarly, a high-tech company may need to collaborate with either internal or external partners to jointly advance a new technology innovation. For example, consider partnership between Tesla and its component supplier Panasonic (described by Hu et al., 2016). Tesla's principal focus is on development of electric cars, which in turn relies on and requires Panasonic's investments to advance its battery technology. Panasonic, on the other hand, might have investment opportunities beyond battery technology and thus would require reducing uncertainty about Tesla's electric car technology before committing to a large investment which is critical for Tesla.

In this chapter we consider optimal decision-making under uncertainty in partnerships. Specifically, we develop a dynamic model aimed at capturing optimal technology adoption and information acquisition decisions in a partnership. (The model captures a generic joint decision-making setting, i.e., deciding on any project with an uncertain reward. Technology adoption is used to provide consistency with the terminology which is prevalent in the literature.) We consider a risk-neutral decision-maker and her risk-neutral partner, who divide responsibilities for different aspects of technology adoption decision-making process for the partnership. The technology, if adopted and if successful, will create positive value for the partnership. However, its success is uncertain. In each discrete-time period, the decision-maker (e.g., startup founder) decides to either adopt/reject the technology for the partnership or delay the adoption decision and request that the partnership acquire costly information which will reduce the uncertainty. This costly information acquisition request requires approval of her partner (e.g., venture capitalist) who either approves it or denies it. If the request is approved, information is acquired (modeled as realization of a binary signal) and the uncertainty about the value of technology is reduced in the next period (joint belief is updated in a Bayesian fashion).

Note that if the decision-maker has no partner, our setting readily reduces to the classical single decision-maker model of McCardle (1985). Therefore, when analyzing the performance of the optimal policy for the partnership, we use this single decision-maker policy (hereafter, the SDM policy) as a natural benchmark. However, we establish that partners' value functions are generically non-convex, and thus the optimal policy for the partnership is more complex than and structurally different from any SDM policy,

An important feature of the decision problem for the partnership is that the decision-maker and her partner might have a different value for the adopted successful technology (while both have zero value if it fails). Furthermore, the model allows for one-time investment (setup) costs and per-signal information acquisition costs to be different for the decision-maker and her partner. Thus, our model, formally introduced in Section 4.2, captures not just asymmetry in decision-making responsibilities, but also asymmetry in revenues and costs. We establish that the latter asymmetry is dictating the structure of the optimal policy for the partnership. Absent this asymmetry, i.e., when the decision-maker and her partner have proportional revenues and costs, we show in Section 4.2.3 that the optimal policy for the partnership coincides with the SDM policy (i.e., as if all partnership decisions are made by one party). Moreover, we show that a possible difference in information acquisition costs incurred by partners does not affect the structure of the optimal policy for the partnership: if the decision-maker and her partner have equal value of technology and equal one-time investment cost, then the optimal policy is the SDM policy of the party which incurs higher per-signal information acquisition cost.

In Section 4.3 we analyze the structure of the optimal policy for a partnership, without the restriction that the decision-maker and her partner have proportional revenues and costs. We establish that the structure of the optimal policy for a partnership is generically different from the SDM policy. Specifically, the optimal policy for the partnership could be non-monotonic in the probability of the technology's success. While in the SDM policy, for any precision of the prior distribution of the technology's success probability, there exist two thresholds such that the technology is adopted if the belief about technology success is above the upper threshold and is rejected if the belief is below the lower threshold value, an optimal policy for the partnership has a more complex structure (due to the non-convexity of the partners' value functions) and may not be characterized by such thresholds. For example, non-monotonicity of the optimal policy for the partnership implies that it could be optimal for the partnership to reject the technology for some high probability of technology success, while at the same precision adopt the technology at a lower probability. Furthermore, the optimal policy for the partnership may include technology adoption or rejection for the partnership that is *premature* compared to the optimal SDM policy (which would suggest information acquisition). Such premature decisions could be forced by the partner's denial of the request for information acquisition, but also could be anticipatory of the partnership's decisions under all possible future signal realizations. Moreover, we show that the anticipation of premature decisions in a later period could trigger an *unraveling effect* that leads to a series of premature decisions in earlier periods.

In the remainder of this section, we briefly discuss related literature. The rest of the chapter is organized as follows. In Section 4.2, we introduce our model and benchmark single decision-maker policy McCardle (1985), present basic properties of the optimal policy for the partnership, and provide conditions that ensure that it coincides with an SDM policy. In Section 4.3, we analyze optimal policies for asymmetric partnerships, and compare their structure and performance to the benchmark SDM policy. Specifically, we establish the aforementioned non-monotonicity of the optimal policies, and identify premature adoption and premature rejection decisions due to the unravelling effect. Finally, in Section 4.4, we provide brief concluding remarks. All proofs are relegated to the Appendix.

4.1.1 Related Literature

If a partnership is reduced to a single party, thereby eliminating this chapter's principal research question, our model reduces to the classic model of McCardle (1985), in which a single decision-maker faces a single technology whose value is ex-ante uncertain. There is a body of work extending McCardle (1985) to allow for multiple decision-makers and/or multiple technology choices. For example, Mamer and McCardle (1987) consider two decision-makers, each making an adoption decision on its own technology, with value affected by complementarity or substitutability of the adopted technologies. Similarly, Kornish (2006) examines optimal decisions of multiple independent decision-makers facing two competing and incompatible technologies, each of which is subject to positive network effects. Also, Kornish and Keeney (2008) study the optimal decision of a single decision-maker facing two independent technologies, while Cho and McCardle (2009) allow for dependence in technology values. In contrast to these works, we focus on a single technology adoption decision that needs to be jointly made by decision-makers who are partners, with potentially asymmetric objectives and decision-making responsibilities. Technically, unlike the standard approaches in this literature focusing on optimizing over a single or separable objectives, our approach requires simultaneously optimizing two inseparable objectives.

Our focus on optimizing decisions for the partnership is somewhat reminiscent of the extensive literature on collective/group behavior and decision-making (e.g., Keeney and Kirkwood, 1975; Freimer and Yu, 1976; Eliashberg and Winkler, 1981; Xanthopulos et al., 2000; Baucells and Sarin, 2003; Schilling et al., 2007; Gavirneni and Xia, 2009; Lightle et al., 2009; Dias and Sarabando, 2012; Jose et al., 2013; Keeney, 2013; Lichtendahl Jr et al., 2013; Owen, 2015; Keck et al., 2014; Denant-Boemont et al., 2017). Interestingly, even though a cooperation and coordination among partners is needed to reach optimal decision for the partnership (as typical in aforementioned literature), we show that in our setting analyzing strategic interactions between the partners is critical for establishing optimal decision policies. For this reason, our work could also be viewed as a variation on the strategic experimentation models from microeconomic theory (e.g., Keller et al., 2005; Bergemann and Hege, 2005; Keller and Rady, 2010; Bonatti and Hörner, 2011; Manso, 2011; Gerardi and Maestri, 2012; Gomes et al., 2016). However, unlike these models that exploit informational asymmetries often in a principal-agent framework, a distinctive feature of our model is that there are no informational asymmetries and that asymmetry among partners' costs and expected revenues is exogenous. Interestingly, we show that coordination problems persist even in such setting.

There is a number of papers on other variations and generalizations of the classical McCardle (1985) model (e.g., Lippman and McCardle, 1987, 1991; Krishnan and Bhattacharya, 2002; Erat and Kavadias, 2006; Lim et al., 2006; Ulu and Smith, 2009; Cho, 2010; Kwon, 2010; Kwon and Lippman, 2011; Smith and Ulu, 2012; Bhattacharjya and Deleris, 2014; Massala and Tsetlin, 2015; Zorc and Tsetlin, 2017). Our work contributes to this literature as it identifies impact on the structural properties of the optimal policy. Specifically, we establish that due to strategic interactions among partners, value functions may not be continuous, optimization problem is non-convex, and consequently the optimal policy may be non-monotonic. Thus, we show that decision-making in a partnership impacts the structure of the basic SDM policy as it may require the optimal policy to be non-monotonic. (Non-monotonicity of optimal technology adoption policy has also been established in, e.g., Smith and Ulu, 2017, who analyze the impact of decision-maker's risk attitudes.)

4.2 Technology Adoption in a Partnership

We consider a risk-neutral decision-maker A (which we refer to as "she") and her risk-neutral partner B (which we refer to as "he") jointly deciding whether to adopt or reject a new technology for their partnership. The new technology may create a positive value for the partnership, but its success is uncertain. The uncertainty is measured by the success probability of the new technology δ.

A and B have a Beta(α, β) distributed common prior belief of the success probability δ. Hence, the point estimate of δ is given by $E[\delta|\alpha, \beta] = \alpha/(\alpha + \beta)$. In each discrete time period i, the partnership could choose to update their belief by acquiring information in the form of binary (i.e., either positive or negative) signals $X_i \sim Ber(\delta)$. Note that α can be interpreted as the total number of positive signals received and β can be interpreted as the total number of negative signals received. Specifically, if the partnership acquires new information and a positive signal is received, their updated belief is Beta$(\alpha+1, \beta)$, and if a negative signal is received, their updated belief is Beta$(\alpha, \beta+1)$. In addition, we use standard notation $\tau = \alpha + \beta$ to represent the precision of the partnership's estimate. (The precision $\tau = \alpha + \beta$ can be interpreted as the total amount of information acquired; the precision increases as the total amount of information acquired increases.)

Partners have different decision-making responsibilities: A is in charge of making the technology adoption decision for the partnership, while B approves any costly information acquisition. Specifically, in each discrete-time period i, A either makes a terminal decision to adopt ("AD") or reject ("RJ") the technology for the partnership, or requests her partner B's approval to acquire additional information on δ. Note that B only has a decision to make in the latter case: he either approves A's request for information acquisition ("Y") or denies it ("N"). If B approves A's request, A and B update their common belief based on the received signal X_i ("CT"), and A faces the same decision choices in the next period $i+1$. However, if B denies A's request, no information is acquired, and the decision is passed back to A in the next period $i+1$. The sequence of decisions is depicted in Figure 4.1.[1]

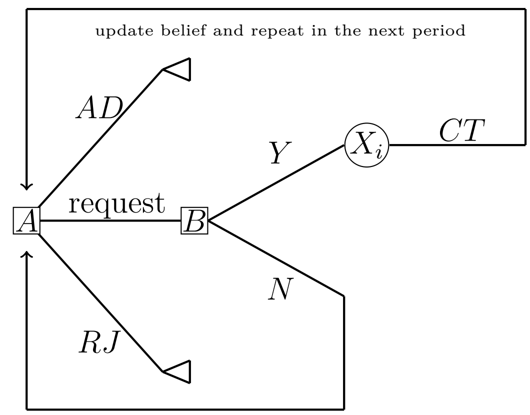

FIGURE 4.1: Sequence of decisions in one time period

In summary, there are three possible decisions for the partnership in each time period, namely, "information acquisition", "technology adoption", and "technology rejection".

Partners' stakes need not be equal and this is captured by potentially different share of revenues and costs for each decision. If the partnership decides on information acquisition in time period i, the cost of acquiring signal X_i incurred by A and B is c_A and c_B, respectively. In the case of technology adoption (terminal decision), A and B incur one-time technology setup costs, K_A and K_B, respectively. A and B's respective one-time revenues from the adopted technology are P_A and P_B if the technology succeeds, while both parties receive 0 if it fails. In the case of technology rejection (terminal decision), A and B resort to their outside options, and without loss of generality, we normalize the payoffs from their outside options to 0. Thus,

[1] Note that we consider the model without time discounting.

given the success probability δ, the respective expected values of technology for A and B are

$$\pi_A(\delta) = \delta P_A - K_A \text{ and } \pi_B(\delta) = \delta P_B - K_B. \tag{4.1}$$

Using $E[\delta|\alpha, \beta] = \alpha/(\alpha + \beta)$, and due to the linearity of the payoff functions, the respective expected values of the technology for A and B are

$$\pi_A(\alpha, \beta) = \frac{\alpha}{\alpha + \beta} P_A - K_A \text{ and } \pi_B(\alpha, \beta) = \frac{\alpha}{\alpha + \beta} P_B - K_B. \tag{4.2}$$

Proposition 12. *If it is optimal for B to deny A's request for information acquisition in period i, it is optimal for A to make a terminal decision in any period $i' \geqslant i$.*

Proof. Since costs and revenues do not change over time, and absent new information the partnership's belief Beta(α, β) remains unchanged, it would also be optimal for B to deny A's request for information acquisition in any period $i' > i$. Consequently, once A's request for information acquisition is denied, there will be no change in partnership belief or revenues or costs for any period $i' \geqslant i$ (i.e., after period $i - 1$ which was the last period in which information have been acquired), until the period in which A makes a terminal decision. Hence, since costs and revenues related to a terminal decision are not time-dependent, it is optimal for A to make a terminal decision in any period $i' \geqslant i$. □

Since revenues and costs are fixed, it follows that B can force A to make a terminal decision.[2] In addition, note that the revenues and costs of A and B are known to both parties so A could anticipate whether B would approve or deny her request for information acquisition. Thus, given Proposition 12, A would only request

[2] We simply rule out the degenerate and uninteresting situation in which all A's repetitive requests for information acquisition are denied by B, resulting in inconsequential postponement of a terminal decision.

for information acquisition if she anticipates that B would approve her request. Therefore, on the optimal decision path, A's decision of "requesting information acquisition" is equivalent to "information acquistion" for the partnership. Thus, when we present A's optimal policy for the partnership, we slightly abuse the notation and without loss of generality use "CT", which formally represents "information acquistion", to denote "requesting information acquisition".

4.2.1 Coupled Decision Problems

Let Beta(α, β) be the partnership's belief about δ. We denote A and B's respective value functions as

$$V_A(\alpha, \beta) \quad \text{and} \quad V_B(\alpha, \beta). \tag{4.3}$$

Similarly, we denote the respective values for A and B, if additional information is acquired and the decision is postponed to a later period, as

$$\Delta_A(\alpha, \beta) = -c_A + \frac{\alpha}{\alpha + \beta} V_A(\alpha + 1, \beta) + (1 - \frac{\alpha}{\alpha + \beta}) V_A(\alpha, \beta + 1) \tag{4.4}$$

and

$$\Delta_B(\alpha, \beta) = -c_B + \frac{\alpha}{\alpha + \beta} V_B(\alpha + 1, \beta) + (1 - \frac{\alpha}{\alpha + \beta}) V_B(\alpha, \beta + 1), \tag{4.5}$$

where c_A and c_B are A and B's respective cost of acquiring information in the current period, and $\frac{\alpha}{\alpha+\beta} V_A(\alpha + 1, \beta) + (1 - \frac{\alpha}{\alpha+\beta}) V_A(\alpha, \beta + 1)$ and $\frac{\alpha}{\alpha+\beta} V_B(\alpha + 1, \beta) + (1 - \frac{\alpha}{\alpha+\beta}) V_B(\alpha, \beta + 1)$ are A and B's respective expected returns in the next period.

If A requests information acquisition, B's optimal value is given by

$$\max\{\pi_B(\alpha, \beta) \mathbb{1}_{(\pi_A(\alpha,\beta)>0)}, \Delta_B(\alpha, \beta)\}, \tag{4.6}$$

Note that the first term $\pi_B(\alpha, \beta) \mathbb{1}_{(\pi_A(\alpha,\beta)>0)}$ is B's return if he denies A's request for information acquisition. Specifically, in such case B's return depends on A's preference over terminal decisions of technology adoption and technology rejection: if A prefers adoption to rejection (i.e., $\mathbb{1}_{(\pi_A(\alpha,\beta)>0)} = 1$), then B's payoff is $\pi_B(\alpha, \beta)$. Whereas, if A prefers rejection to adoption (i.e., $\mathbb{1}_{(\pi_A(\alpha,\beta)>0)} = 0$), then B's payoff is 0. On the other hand, the second term $\Delta_B(\alpha, \beta)$ is B's expected return if he approves A's request for information acquisition.

If A anticipates that B would approve her request for information acquisition, A could either adopt the technology, reject the technology, or request for information acquisition. Thus, her optimal value is given by

$$\max\{\pi_A(\alpha, \beta), 0, \Delta_A(\alpha, \beta)\}, \tag{4.7}$$

where the first term $\pi_A(\alpha, \beta)$ is A's return if she adopts the technology, The second term 0 corresponds to A's return if she rejects the technology, and the third term $\Delta_A(\alpha, \beta)$ is A's return if she requests information acquisition (and B approves it).

If A anticipates that B would deny her request for information acquisition, A's optimal value would reduce to the higher of the two values corresponding to the terminal decisions:

$$\max\{\pi_A(\alpha, \beta), 0\}. \tag{4.8}$$

Therefore, combining (4.6), (4.7), and (4.8), A's value function can be expressed as

$$V_A(\alpha, \beta) = \max\{\pi_A(\alpha, \beta), 0, \Delta_A(\alpha, \beta)\mathbb{1}_{(\Delta_B(\alpha,\beta)>\pi_B(\alpha,\beta)\mathbb{1}_{(\pi_A(\alpha,\beta)>0)})}\}. \tag{4.9}$$

Note that the third term $\Delta_A(\alpha, \beta)\mathbb{1}_{(\Delta_B(\alpha,\beta)>\pi_B(\alpha,\beta)\mathbb{1}_{(\pi_A(\alpha,\beta)>0)})}$ captures A's option of requesting information acquisition. Specifically, the viability of information acquisition depends on B's decision: if B would approve A's request, information acquisition would be viable, and the third term becomes the expected return for A if she requests information acquisition, i.e., $\Delta_B(\alpha, \beta)$. Whereas, if B would deny A's request, information acquisition cannot be optimal because the third term becomes 0.

On the other hand, B's value function can be expressed as

$$\begin{aligned} V_B(\alpha,\beta) &= \max\{\pi_B(\alpha,\beta)\mathbb{1}_{(\pi_A(\alpha,\beta)>0)}, \Delta_B(\alpha,\beta)\}\mathbb{1}_{(\Delta_A(\alpha,\beta))>\max\{\pi_A(\alpha,\beta),0\})} \\ &\quad + \pi_B(\alpha,\beta)\mathbb{1}_{(\pi_A(\alpha,\beta)>0)}(1-\mathbb{1}_{(\Delta_A(\alpha,\beta))>\max\{\pi_A(\alpha,\beta),0\})}). \end{aligned} \tag{4.10}$$

Note that B's return depends on whether A would request information acquisition. Specifically, if additional information is valuable to A, A would potentially request information acquisition. Thus, B's decision is to determine whether additional information is also valuable to him (i.e., whether to approve should A request), and consequently, his return is given by comparing the return of information acquisition and the termination payoff, i.e., $\max\{\pi_B(\alpha,\beta)\mathbb{1}_{(\pi_A(\alpha,\beta)>0)}, \Delta_B(\alpha,\beta)\}$. On the other hand, if additional information is not valuable to A (i.e., $1-\mathbb{1}_{(\Delta_A(\alpha,\beta))>\max\{\pi_A(\alpha,\beta),0\})} = 1$), A would not request information acquisition, and thus B has no decision to make and his return is the termination payoff, i.e., $\pi_B(\alpha,\beta)\mathbb{1}_{(\pi_A(\alpha,\beta)>0)}$.

Note that the indicator functions in the coupled dynamic programs (4.9) and (4.10), may lead to discontinuities. In turn, these discontinuities may induce non-convexity of the value functions and, consequently, non-monotonicity and a complex structure of the optimal policy for the partnership, as discussed in detail in Section 4.3.

4.2.2 Single Decision-Maker Benchmark

Note that absent of her partner B (e.g., as if B had no stake on its own and would automatically approve every A's request for information acquisition), A's decision problem is equivalent to that of the single decision-maker in McCardle (1985). However, A and B's different stakes in the partnership (i.e., revenues and costs) have non-trivial impact on A's decision-making. In this work, we characterize this impact by comparing A's optimal policy for the partnership in our setting, with that established in McCardle (1985), i.e., the setting in which A is the only decision maker.

To that end, we use A's optimal policy established in the single decision-maker setting in McCardle (1985) as the benchmark for comparison. Specifically, given revenues from adopted (successful) technology P_A, one-time technology setup costs K_A, and cost of acquiring signal X_i, c_A, we denote the single decision-maker policy, as $SDM(P_A, K_A, c_A)$. The following proposition that follows directly from McCardle (1985) gives a complete characterization of $SDM(P_A, K_A, c_A)$.

Proposition 13 (Single Decision-Maker Policy, McCardle (1985))**.** *Given P_A, K_A, and c_A, A's optimal policy $SDM(P_A, K_A, c_A)$ in terms of precision $\tau = \alpha + \beta$ is characterized by a non-decreasing threshold function $\underline{\pi}_A(\tau)$ and non-increasing threshold function $\bar{\pi}_A(\tau)$, with $0 \leqslant \underline{\pi}_A \leqslant \bar{\pi}_A$.*

(i) It is optimal for A to reject the new technology if and only if $\pi_A(\alpha, \beta) \leqslant \underline{\pi}_A(\tau)$.

(ii) It is optimal for A to acquire information if and only if $\underline{\pi}_A(\tau) \leqslant \pi_A(\alpha, \beta) \leqslant \bar{\pi}_A(\tau)$.

(iii) It is optimal for A to adopt the new technology if and only if $\bar{\pi}_A(\tau) \leqslant \pi_A(\alpha, \beta)$.

Furthermore, A's optimal policy has a finite stopping time: there exists a finite N_{SDM} such that A reaches a terminal decision by period N_{SDM}.

The $SDM(P_A, K_A, c_A)$ policy is depicted in Figure 4.2. Here the x-axis corresponds to the precision $\tau = \alpha + \beta$ and the y-axis represents the expected value of technology $\pi_A = \frac{\alpha}{\alpha+\beta} P_A - K_A$. A's beliefs can be represented by a point in this figure and will move from left to right as she acquires information.

4.2.3 Basic Properties of the Optimal Policy

In this section we establish some basic properties of A's optimal policy for the partnership in our model.

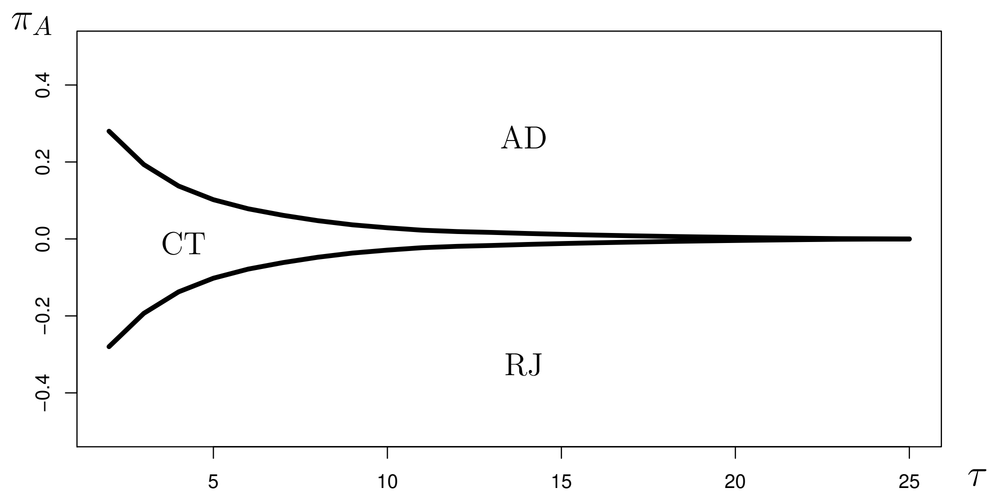

FIGURE 4.2: A's optimal single decision-maker policy: $SDM(P_A, K_A, c_A)$

We first note the existence of the finite stopping time, i.e., the partnership reaches a terminal decision (and stops information acquisition) after finite number of periods. Furthermore, the partnership reaches a terminal decision no later than the single decision maker following optimal policy $SDM(P_A, K_A, c_A)$.

Proposition 14 (Finite Stopping Time)**.** *There exists $N_P \leqslant N_{SDM}$ such that A's optimal policy for the partnership reaches a terminal decision by period N_P.*

Proof. If it is optimal for A to make a terminal decision according to $SDM(P_A, K_A, c_A)$, then it is optimal for A to make a terminal decision for the partnership (which does not need B's approval). Hence, the result follows directly from Proposition 13. □

Next, we show that A's optimal policy for the partnership coincides with the single decision-maker policy $SDM(P_A, K_A, c_A)$, whenever A and B' costs and revenues are proportional (i.e., A and B's revenue and cost ratios are the same, $P_A/P_B = K_A/K_B = c_A/c_B$).

Proposition 15. *If $P_A/P_B = K_A/K_B = c_A/c_B$, then A's optimal policy for the partnership is the $SDM(P_A, K_A, c_A)$ policy.*

Proof. Let $\gamma = P_A/P_B = K_A/K_B = c_A/c_B$. Due to the linearity of payoff functions, given by (4.2), (4.4) and (4.5), for any α and β, we have

$$\gamma = \frac{\pi_A(\alpha, \beta)}{\pi_B(\alpha, \beta)} = \frac{\Delta_A(\alpha, \beta)}{\Delta_B(\alpha, \beta)}.$$

Thus, from (4.9), we have

$$\begin{aligned}
V_A(\alpha, \beta) &= \max\{\pi_A(\alpha, \beta), 0, \Delta_A(\alpha, \beta)\mathbb{1}_{(\Delta_B(\alpha,\beta) > \pi_B(\alpha,\beta)\mathbb{1}_{(\pi_A(\alpha,\beta)>0)})}\} \\
&= \max\{\pi_A(\alpha, \beta), 0, \Delta_A(\alpha, \beta)\mathbb{1}_{(\frac{\Delta_A(\alpha,\beta)}{\gamma} > \frac{\pi_A(\alpha,\beta)}{\gamma}\mathbb{1}_{(\pi_A(\alpha,\beta)>0)})}\} \\
&= \max\{\pi_A(\alpha, \beta), 0, \Delta_A(\alpha, \beta)\mathbb{1}_{(\Delta_A(\alpha,\beta) > \pi_A(\alpha,\beta)\mathbb{1}_{(\pi_A(\alpha,\beta)>0)})}\} \\
&= \max\{\pi_A(\alpha, \beta), 0, \Delta_A(\alpha, \beta)\}.
\end{aligned}$$

Therefore, we have shown that B would approve A's request for information acquisition at any time and thus A's problem is the same as in the SDM problem. □

Interestingly, as we establish next, A's optimal policy for the partnership is reminiscent of a single decision-maker policy, provided that A and B's one-time technology adoption revenues and set-up costs are proportional, $P_A/P_B = K_A/K_B$. Any asymmetry in information acquisition costs c_A and c_B determines the parameters of the single decision-maker policy that defines A's optimal policy for the partnership.

Proposition 16. *Let $\theta = P_A/P_B = K_A/K_B$ and $\gamma = c_A/c_B$, with $\theta \neq \gamma$.*

(i) If $\gamma < \theta$, A's optimal policy for the partnership is $SDM(P_B, K_B, c_B)$.

(ii) If $\gamma > \theta$, A's optimal policy for the partnership is $SDM(P_A, K_A, c_A)$.

Proof. Similar as in the proof of Proposition 15, due to the linearity of payoff functions, given by (4.2), for any α and β, we have

$$\theta = \frac{\pi_A(\alpha, \beta)}{\pi_B(\alpha, \beta)}.$$

Therefore, A and B's preference over adoption and rejection are the same, i.e., $\pi_A(\alpha, \beta) > 0$ if and only if $\pi_B(\alpha, \beta) = \frac{\pi_A(\alpha,\beta)}{\gamma} > 0$. Thus, from (4.9), we have

$$\begin{aligned} V_A(\alpha, \beta) &= \max\{\pi_A(\alpha, \beta), 0, \Delta_A(\alpha, \beta)\mathbb{1}_{(\Delta_B(\alpha,\beta)>\pi_B(\alpha,\beta)\mathbb{1}_{(\pi_A(\alpha,\beta)>0)})}\} \\ &= \max\{\pi_A(\alpha, \beta), 0, \Delta_A(\alpha, \beta)\mathbb{1}_{(\Delta_B(\alpha,\beta)>\pi_B(\alpha,\beta)\mathbb{1}_{(\pi_B(\alpha,\beta)>0)})}\}. \end{aligned} \tag{4.11}$$

Since their preferences over adoption and rejection are the same, the decision revolving information acquisition solely depends on the difference of A and B's information costs. Specifically, from (4.4) and (4.5), we have

i) when $\gamma < \theta$, if it is optimal for B to acquire additional information, then it is optimal for A to acquire additional information, i.e., if $\Delta_B(\alpha, \beta) > \pi_B(\alpha, \beta)\mathbb{1}_{(\pi_B(\alpha,\beta)>0)}$, then $\Delta_A(\alpha, \beta) > \pi_A(\alpha, \beta)\mathbb{1}_{(\pi_A(\alpha,\beta)>0)}$. However, the converse statement does not always hold true. Therefore, from (4.11), A's optimal policy for the partnership is $SDM(P_B, K_B, c_B)$.

ii) when $\gamma > \theta$, the argument is reversed. In particular, if it is optimal for A to acquire additional information, then it is optimal for B to acquire additional information, i.e., if $\Delta_A(\alpha, \beta) > \pi_A(\alpha, \beta)\mathbb{1}_{(\pi_A(\alpha,\beta)>0)}$, then $\Delta_B(\alpha, \beta) > \pi_B(\alpha, \beta)\mathbb{1}_{(\pi_B(\alpha,\beta)>0)}$. However, the converse statement does not always hold true. Therefore, from (4.11), A's optimal policy for the partnership is $SDM(P_A, K_A, c_A)$.

This completes the proof. □

Proposition 16 extends Proposition 15 and establishes that A's optimal policy for the partnership in which A and B have proportional revenues and setup costs coincides with the SDM policy of the partner who incurs disproportionally higher per-signal information acquisition cost (i.e., the optimal policy for the partnership is as if the partner with higher information acquisition cost were the only decision-maker).

However, a proportional allocation of revenues and costs among partners is crucial for the optimal policy for the partnership to have a structure of a single decision-maker policy. In the next section, we establish that the structure of the optimal policy for the partnership in which revenues and costs are not allocated proportionally among the partners is different than any single decision-maker policy.

4.3 Optimal Policy in an Asymmetric Partnership

In many settings, revenues and costs from technology adoption process might not be allocated proportionally among partners. For example, a venture capital investor might secure a disproportional share of the partnership at the time of their investment. (Early investors might face larger uncertainty and require disproportionally large share of the partnership, while late investors might face less uncertainty and would secure a disproportionally small share relative to existing partners.) In this section we show that such asymmetry between partners' costs and revenues has a profound impact on the structure of the optimal policy for the partnership.

We next demonstrate structural differences between the optimal policy for the partnership and any SDM policy, even in the setting in which costs are equal for the decision maker and her partner, i.e., throughout this section we set

$$K_A/K_B = c_A/c_B = 1. \tag{4.12}$$

Consequently, a possible asymmetry among partners is captured by a single parameter θ that measures ratio of the partners' respective revenues:

$$\theta = P_A/P_B. \tag{4.13}$$

to capture A and B's difference in the revenue from the technology (or equivalently, the expected value of the technology). Note that $\theta = 1$ corresponds to the partnership in which A and B have both equal costs and equal revenues, covered by Proposition 15. In this section, we analyze cases in which $\theta \neq 1$. Specifically, we establish that the difference among the partners' revenues from the technology structurally changes the optimal policy. (In Section 4.3.3, we show that having equal cost assumption 4.12 is without a loss of generality: our results extend to general cost ratios, i.e., $K_A/K_B = c_A/c_B \neq 1$.)

Further, for the analysis in the rest of the chapter, without loss of generality, we normalize A's revenue from the technology to be 1, i.e., $P_A = 1$. Moreover, we fix A's setup cost of the technology at $K_A = 0.5$. Note that $P_A = 1$ and $K_A = 0.5$ set A's break-even probability for technology adoption at $p = 0.5$. Finally, to simplify exposition and ensure that A's information acquisition cost c_A is relatively small compared to A's one-time revenue from the technology adoption $P_A = 1$ and to the one-time technology setup cost $K_A = 0.5$, for concreteness we fix $c_A = 0.01$.

With this notation in place, we will use (θ, α, τ) to denote the state variable; recall that $\tau = \alpha + \beta$ denotes the precision of the beta prior at a given period. Note that (θ, α, τ) is sufficient to compute P_B by (4.13) and π_A and π_B by (4.2). Therefore, in what follows we slightly abuse notation and use α and π_A interchangeably for expositional convenience. Similarly, we use (θ, α, τ) parameters to describe π, V, and Δ defined in (4.2), (4.3), (4.4), and (4.5), so in what follows we also write $\pi_A(\theta, \alpha, \tau)$, $\pi_B(\theta, \alpha, \tau)$, $V_A(\theta, \alpha, \tau)$, $V_B(\theta, \alpha, \tau)$, and $\Delta_A(\theta, \alpha, \tau)$, $\Delta_B(\theta, \alpha, \tau)$.

4.3.1 Non-Monotonicity of the Optimal Policy

Note that a key property of the benchmark SDM policy described in Proposition 13 is that it is monotonic in α (or equivalently, π_A) for any given precision τ. Specifically, there is a natural ordering of decisions: reject $\prec$ acquire information $\prec$ accept, so that for any given τ, the optimal policy that maps α (or equivalently, π_A) to one of these three decisions is non-decreasing with respect to this natural order. More formally,

Definition 6 (Monotonic policy)**.** *A technology adoption policy is monotonic in α if for any precision $\tau(\geqslant \alpha)$, there exist thresholds $\underline{\alpha}$ and $\bar{\alpha}$ so that the decision is*

- *reject if and only if $\alpha \leqslant \underline{\alpha}$,*
- *acquire information if and only if $\underline{\alpha} \leqslant \alpha \leqslant \bar{\alpha}$,*
- *adopt if and only if $\bar{\alpha} \leqslant \alpha$.* □

However, as we show below, the optimal policy for the partnership with $\theta \neq 1$ need not be monotonic. We establish this result by first considering a restricted setting, different from our model, in which A is restricted to make a terminal decision by period $T = 3$. This restriction limits the number of decision scenarios and allows us to fully analyze all decision paths.

Lemma 10. *Suppose that A is required to make a terminal decision by period $T = 3$. There exist a nonempty set Θ such that A's optimal policy is not monotonic if $\theta \in \Theta$.*

Proof. Consider the case in which A and B start in the first period with $\tau = 1$, $1/2 < \alpha < 1$ and $\alpha/2 < 1/2$. Note that A's breakeven probability for termination decision (i.e., between adoption and rejection) is 1/2. This implies that A's optimal termination decision in the first period is to adopt the technology, and her optimal termination decisions in the second period are to adopt the new technology, if receiving a positive signal (+) in the first period, but to reject the technology, if receiving a negative signal (-) in the first period.

When $T = 3$, B might deny A's request information acquisition in the first and second period. (Since the third period is the last period, A cannot request for information acquisition.) First, note that given $1/2 < \alpha < 1$, we have $(\alpha+1)/3 > 1/2$ and $(\alpha + 2)/3 > 1/2$. This implies that, if A receives a positive signal in the first period, A's optimal decision in the third period is to adopt the technology regardless of the signal she receives in the second period. Since additional information would not change A's decision in the third period, it is suboptimal for A to request information acquisition in the second period after receiving a positive signal in the first period. Thus, A's optimal decision is her optimal termination decision, which is to adopt the technology. On the other hand, note that there exists $\alpha \in (1/2, 1)$ such that $\alpha/3 < 1/2$ and $(\alpha + 1)/3 > 1/2$. This implies that, if A receives a negative signal in the first period, A's optimal decision in the third period could be to adopt the technology, if receiving a positive signal in second period, and to reject the technology, if receiving a negative signal in the second period. Since additional information could potentially lead to different optimal decisions in the third period, it could be optimal for A to request information acquisition after receiving a negative signal in the first period.

Next, we analyze A's optimal decisions in the first period. Recall that $\pi_i(\theta, \alpha, \tau)$ denote the payoff of adopting the technology, and $\Delta_i(\theta, \alpha, \tau)$ denote the value of continuing acquiring information. First, consider the situation in which it is optimal for B to approve A's request in the first period, but denies A's request in the second period after receiving a negative signal in the first period, i.e., the situation in which

$$\Delta_B(\alpha, 1) = -0.01 + \alpha(\frac{\alpha + 1}{2\theta} - 0.5) > \frac{\alpha}{\theta} - 0.5 = \pi_B(\alpha, 1), \tag{4.14}$$

and

$$\Delta_B(\alpha, 2) = -0.01 + \frac{\alpha}{2}(\frac{\alpha + 1}{3\theta} - 0.5) < 0. \tag{4.15}$$

When (4.14) and (4.15) hold, it is optimal for A to adopt the technology in the first period if and only if

$$\Delta_A(\alpha, 1) = -0.01 + \alpha(\frac{\alpha+1}{2} - 0.5) < \alpha - 0.5 = \pi_A(\alpha, 1). \tag{4.16}$$

Simultaneously solving (4.14), (4.15) and (4.16), we have $1.1839 < \theta < 1.22667$ and $0.858579 < \alpha < 0.25(3\theta - 2) + 0.05\sqrt{100 - 276\theta + 225\theta^2}$, or $\theta > 1.22667$ and $0.858579 < \alpha < 0.25(\theta + 1) + 0.1\sqrt{25 - 48\theta + 25\theta^2}$.

Next, consider the situation in which B would approve A's request in both the first and the second period after receiving a negative signal in the first period (provided that A would request information acquisition), i.e., the situation in which

$$\Delta_B(\alpha, 1) = -0.01+\alpha(\frac{\alpha+1}{2\theta}-0.5)+(1-\alpha)(-0.01+\frac{\alpha}{2}(\frac{\alpha+1}{3\theta}-0.5)) > \frac{\alpha}{\theta}-0.5 = \pi_B(\alpha, 1), \tag{4.17}$$

and

$$\Delta_B(\alpha, 2) = -0.01 + \frac{\alpha}{2}(\frac{\alpha+1}{3\theta} - 0.5) > 0. \tag{4.18}$$

When (4.17) and (4.18) hold, it is optimal for A to request information acquisition if and only if

$$\Delta_A(\alpha, 1) = -0.01+\alpha(\frac{\alpha+1}{2}-0.5)+(1-\alpha)(-0.01+\frac{\alpha}{2}(\frac{\alpha+1}{3}-0.5)) > \alpha-0.5 = \pi_A(\alpha, 1), \tag{4.19}$$

and

$$\Delta_A(\alpha, 2) = -0.01 + \frac{\alpha}{2}(\frac{\alpha+1}{3} - 0.5) > 0. \tag{4.20}$$

Simultaneously solving (4.17), (4.18), (4.19) and (4.20), we have $0.4445 < \theta < 1$ and $0.6 < \alpha < 0.25(3\theta + 2) - 0.05\sqrt{100 - 276\theta + 225\theta^2}$, or $1 < \theta < 1.21277$ and $0.25(3\theta - 2) + 0.05\sqrt{100 - 276\theta + 225\theta^2} < \alpha < 0.9$.

On the other hand, when (4.17), (4.18) and (4.20) are hold, it is optimal for A

to adopt the technology if and only if

$$\Delta_A(\alpha,1) = -0.01+\alpha(\frac{\alpha+1}{2}-0.5)+(1-\alpha)(-0.01+\frac{\alpha}{2}(\frac{\alpha+1}{3}-0.5)) < \alpha-0.5 = \pi_A(\alpha,1). \tag{4.21}$$

Simultaneously solving (4.17), (4.18), (4.20) and (4.21), we have $1 < \theta < 1.21277$ and $0.9 < \alpha < 0.25(3\theta+2)-0.05\sqrt{100-276\theta+225\theta^2}$, or $1.21277 < \theta < 1.22667$ and $0.25(3\theta-2)+0.05\sqrt{100-276\theta+225\theta^2} < \alpha < 0.25(3\theta+2)-0.05\sqrt{100-276\theta+225\theta^2}$.

Combining all the above ranges in θ, we conclude that for

$$\theta \in (1.1839, 1.21277), \tag{4.22}$$

A's optimal decision is to adopt the technology, if $0.858579 < \alpha < 0.25(3\theta-2) + 0.05\sqrt{100-276\theta+225\theta^2}$ and $0.9 < \alpha < 0.25(3\theta+2) - 0.05\sqrt{100-276\theta+225\theta^2}$. However, A's optimal decision for $0.25(3\theta-2)+0.05\sqrt{100-276\theta+225\theta^2} < \alpha < 0.9$ is to request information acquisition (and B would approve the request).

This completes the proof. □

Remark 1. *Note that an analogous argument to that of the proof of Lemma 10 readily establishes non-monotonicity of the optimal policy for*

$$\theta \in (\frac{1}{1.21277}, \frac{1}{1.1839}), \tag{4.23}$$

by carefully adjusting $\alpha > 1$ and reversing above inequalities. Furthermore, the analysis in the proof is not characterizing all θ for which Lemma 10 holds. □

The proof of Lemma 10 and Remark 1, establish that set Θ contains intervals of possible θ values for which Lemma 10 holds (e.g., (4.22) and (4.23)). We next leverage Lemma 10 to establish that the optimal policy for the partnership (without restrictions on stopping time) need not be monotonic.

Proposition 17. *There exists a nonempty set Θ^* such that the optimal policy for the partnership is not monotonic if $\theta \in \Theta^*$.*

Proof. First note that if the optimal policy for the partnership with θ satisfying Lemma 10 would guarantee a terminal decision in at most three periods, i.e., if the stopping time $N_P \leqslant 3$, Lemma 10 readily establishes the result. Similarly, if α and τ satisfy conditions from the proof of Lemma 10 in period $N_P - 3$, the result also readily follows. Hence, we just need to establish existence of such settings, noting that it is possible for θ not to belong to the range identified in the proof of Lemma 10 and still yield a non-monotonic optimal policy (as mentioned in Remark 1).

Here we establish the result with one such θ, $\theta = 5/4$, and $\tau = 3$.

For $\alpha = 1.8$, B's optimal decision is to approve A's request, and A's optimal decision is to request, as

$$\Delta_A(1.25, 1.8, 3) = 0.11 > 0.1 = \pi_A(1.25, 1.8, 3), \tag{4.24}$$

and

$$\Delta_B(1.25, 1.8, 3) = 0.026 > -0.02 = \pi_B(1.25, 1.8, 3). \tag{4.25}$$

For $\alpha = 1.95$, B's optimal decision is to approve A's request, but A's optimal decision is to adopt the technology, as

$$\Delta_A(1.25, 1.95, 3) = 0.144 < 0.15 = \pi_A(1.25, 1.95, 3), \tag{4.26}$$

and

$$\Delta_B(1.25, 1.95, 3) = 0.0485 > 0.02 = \pi_B(1.25, 1.95, 3). \tag{4.27}$$

For $\alpha = 2$, B's optimal decision is to approve A's request, and A's optimal decision is to request, as

$$\Delta_A(1.25, 2, 3) = 0.17 > 0.167 = \pi_A(1.25, 2, 3), \tag{4.28}$$

and

$$\Delta_B(1.25, 2, 3) = 0.0529 > 0.0333 = \pi_B(1.25, 2, 3). \tag{4.29}$$

For $\alpha = 2.5$, B's optimal decision is to deny A's request, and A's optimal decision is to adopt the technology, as

$$\Delta_A(1.25, 2.5, 3) = 0.324 < 0.333 = \pi_A(1.25, 2.5, 3), \tag{4.30}$$

and

$$\Delta_B(1.25, 2.5, 3) = 0.16 < 0.167 = \pi_B(1.25, 2.5, 3). \tag{4.31}$$

This completes the proof. □

Remark 2. *Note that Proposition 17 holds for a range of asymmetric partnerships, e.g.,* $\theta = 4/5$ *as illustrated in Example 8 and 9. Also, non-monotonicity of an optimal policy follows even when there is just a single inner region (unlike two inner regions with* $\theta = 4/5$ *mentioned above and with* $\theta = 5/4$ *described in Example 6). It can be established that optimal policies for partnerships with* $\theta = 2/3$ *and* $\theta = 3/2$ *have such non-monotonic structure.* □

Non-monotonicity of the optimal policy for the partnership stems out of the non-convexity of the problem. Furthermore, because decision problems of A and B cannot generically be decoupled, characterization of the optimal policy for the partnership is challenging to establish analytically (due to discontinuity). Nevertheless, we demonstrate in Proposition 17 that it is structurally different than any SDM policy.

We next illustrate the structure of a non-monotonic optimal policy for the partnership.

Example 5. *Consider a partnership with* $\theta = 5/4$*. The optimal policy for the partnership is overlaid on the benchmark SDM policy (which is characterized by the two outer dashed line thresholds) and depicted in Figure 4.3. In this case, optimal decisions for the partnership contain two inner regions (which correspond to the two*

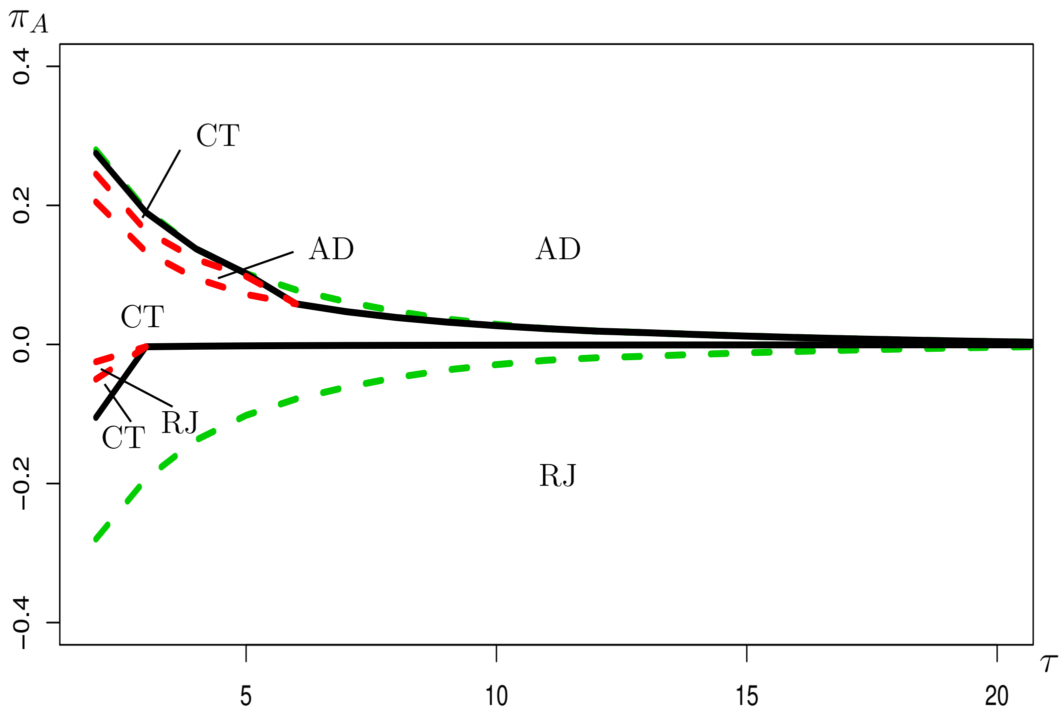

FIGURE 4.3: Optimal policy regions for $\theta = 5/4$

dashed-line regions in Figure 4.3) contained within the two asymmetric outer thresholds (which correspond to the two solid lines in Figure 4.3). Specifically, the upper inner region is an adoption region, i.e., in the region A makes a terminal decision to adopt (AD) the technology for the partnership. On the other hand, the lower inner region is a rejection region, i.e., in that region A makes a terminal decision to reject (RJ) the technology for the partnership. All the other regions within the two asymmetric outer solid-line thresholds are continuation regions, i.e., in those regions partnership decides to acquire information (CT). Thus, with $\tau = 2$ for one concrete example, increasing α from 0 to τ in turn increases π_A which is y-axis in Figure 4.3, and results in the changes of optimal decision in the following order: reject, acquire *information, reject, acquire information, adopt, acquire information, adopt. Hence, the optimal policy for the partnership is not monotone.* ▫

The structure of the optimal policy described in Example 5 is generic for asymmetric partnerships. For example, the structure of optimal policy for the partnership with $\theta = 4/5$ is depicted in Figure 4.7.

Corollary 1. *There exist nonempty set Θ^*, such that for $\theta \in \Theta^*$ the optimal policy for the partnership does not coincide with any SDM policy.*

Corollary 1 follows directly from Proposition 13 and Proposition 17, since every SDM policy is monotonic, while the optimal policy for the partnership may not be. Mathematically, this is due to the non-convexity induced by discontinuities of the value functions, as discussed in Examples 6 and 7, and illustrated in Figures 4.4 and 4.5. (Note that convexity plays a central role in establishing a simple two-threshold structure of the SDM policy from Proposition 13.)

4.3.2 Premature Decisions and Unraveling

We now discuss properties of the optimal policy for the partnership and provide insights that shed light on why its structure is more complex than the structure of the SDM policy. Emergence of the inner adoption and rejection regions described in Example 5 is due to premature terminal decisions which are formally defined next. (Recall that Proposition 14 establishes that A never delays a terminal decision relative to A's SDM(P_A, K_A, c_A) policy.)

Definition 7 (Premature Adoption/Rejection)**.** *A makes a premature adoption (rejection) decision for the partnership if A's optimal SDM(P_A, K_A, c_A) policy decision would have been to acquire information.* ▫

The following example describes and discusses emergence of premature adoption in the optimal policy for the partnership.

Example 6. *Consider the optimal policy for the partnership described in Example 5. Let* $\alpha = 1.95$ *and* $\tau = 3$*. First note that A's SDM optimal policy is to acquire information, as* $\Delta_A(1, 1.95, 3) = 0.157 > 0.15 = \pi_A$*(1, 1.95, 3). (Due to Proposition 15, SDM policy payouts and values correspond to setting* $\theta = 1$*.) Also note that if A were to make a request for partnership to acquire additional information, B would approve it because* $\Delta_B(1.25, 1.95, 3) = 0.0485 > 0.02 = \pi_B(1.25, 1.95, 3)$*. However, it is not optimal for A to request information acquisition, as* $\Delta_A(1.25, 1.95, 3) = 0.144 < 0.15 = \pi_A(1.25, 1.95, 3)$*. This is due to A's continuation value being larger in the SDM setting than in the partnership setting, i.e.,* $\Delta_A(1, 1.95, 3) = 0.157 > 0.144 = \Delta_A(1.25, 1.95, 3)$*. Specifically, if A were to acquire information and a negative signal were received (resulting in no change of* $\alpha = 1.95$ *and in unit increase of precision* $\tau = 3 + 1 = 4$*), A would then want to acquire an additional signal, as* $\Delta_A(1.25, 1.95, 4) = 0.0339 > 0 > -0.0125 = \pi_A(1.25, 1.95, 4)$*. However, should A make this request, B would deny it, as* $\Delta_B(1.25, 1.95, 4) = -0.0236 < 0$*. (On the other hand, if a positive signal were received, A would adopt the technology.) Thus, B's denial of any subsequent information acquisition requests is accounted for in* $\Delta_A(1.25, 1.95, 3)$*. Because A will not be able to acquire subsequent information, it is optimal for A not to acquire information now, and instead prematurely adopt the technology for the partnership.*

Figure 4.4 shows A's values associated with the terminal decision to adopt the technology (AD) and the decision to acquire additional information assuming that B would approve that particular request (CT), as functions of α *around the premature adoption region given* $\tau = 3$*. (This corresponds to part of the vertical slice at* $\tau = 3$ *in Figure 4.3, after converting* α *to A's expected value of the technology* π_A*, as discussed at the beginning of this section.) Note that A's value associated with acquiring additional information has a discontinuity at* $\alpha = 2$*. (This discontinuity results in non-convexity of value functions, which indicates that the optimal policy*

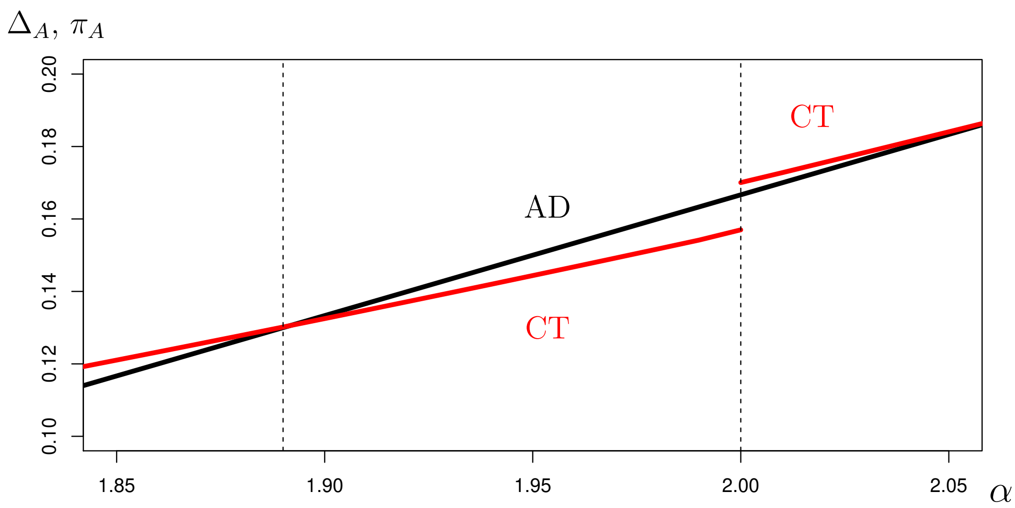

FIGURE 4.4: Premature adoption: A's values of AD and CT for $\theta = 5/4$, $\alpha = 1.95$ and $\tau = 3$

might be structurally different than any SDM policy.) Specifically, for $\alpha > 2$, B would approve a subsequent request for additional information acquisition. For $\alpha < 2$, B would deny any subsequent requests, thereby reducing A's continuation value. This leads to the premature adoption region marked by the two dashed vertical lines. $\square$

We next illustrate emergence of premature rejection in the optimal policy for the same partnership.

Example 7. *Consider again the optimal policy for the partnership described in Example 5, but now let $\alpha = 0.95$ and $\tau = 2$. First note that A's SDM policy is to acquire information, as $\Delta_A(1, 0.95, 2) = 0.065 > 0$. Also note that A would prefer for the partnership to acquire information rather than reject the technology, as $\Delta_A(1.25, 0.95, 2) = 0.0613 > 0$. However, if A were to request information acquisition, B would deny it as $\Delta_B(1.25, 0.95, 2) = -0.0005 < 0$. Note that B's denial of A's request is accounted for a possible A's premature adoption decision in the subsequent period which was described and discussed in Example 6: if B were to approve*

A's request and if a positive signal were received, this would result in increase of both $\alpha = 0.95 + 1 = 1.95$ *and* $\tau = 2 + 1 = 3$*, which is the setting of Example 6. Since it is optimal for B to deny A's request at* $\tau = 2$*, it follows that A's optimal decision for the partnership is to prematurely reject the technology.*

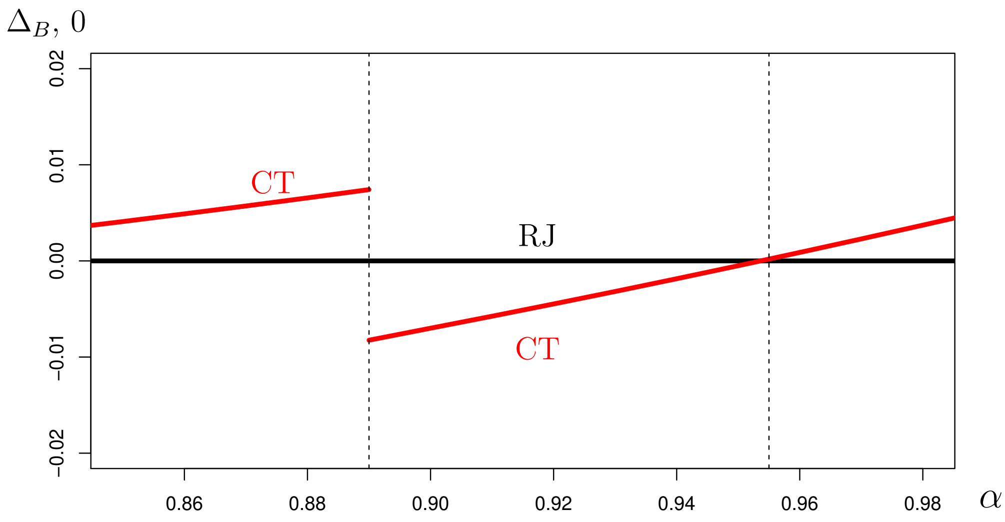

FIGURE 4.5: Premature rejection: B's values of RJ and CT in α for $\theta = 5/4$ and $\tau = 2$

Figure 4.5 shows B's values associated with the terminal decision to reject the the technology (RJ), which is A's optimal terminal decision, and with the decision to acquire additional information provided that A would request it, as functions of α *around the premature rejection region given* $\tau = 2$*. (Figure 4.5 corresponds to part of the vertical slice at* $\tau = 2$ *in Figure 4.3, analogous to description of Figure 4.4 in Example 6.) Note that B's value associated with acquiring additional information has a discontinuity at* $\alpha = 0.89$*. Similar to the discussion in Example 6, this discontinuity leads to non-convexity of the value functions (and thus non-monotonicity of the optimal policy), and is due to the anticipated A's premature adoption decision in the case of a positive signal realization, thereby reducing B's continuation value.*

This in turn leads to A prematurely rejecting the technology for values of α that fall between two dashed vertical lines. □

Example 6 and Example 7 of premature terminal decisions for the partnership with $\theta = 5/4$ establish the following result.

Proposition 18. *Optimal policy in a partnership with $\theta \neq 1$ may include premature rejection and premature adoption decisions.*

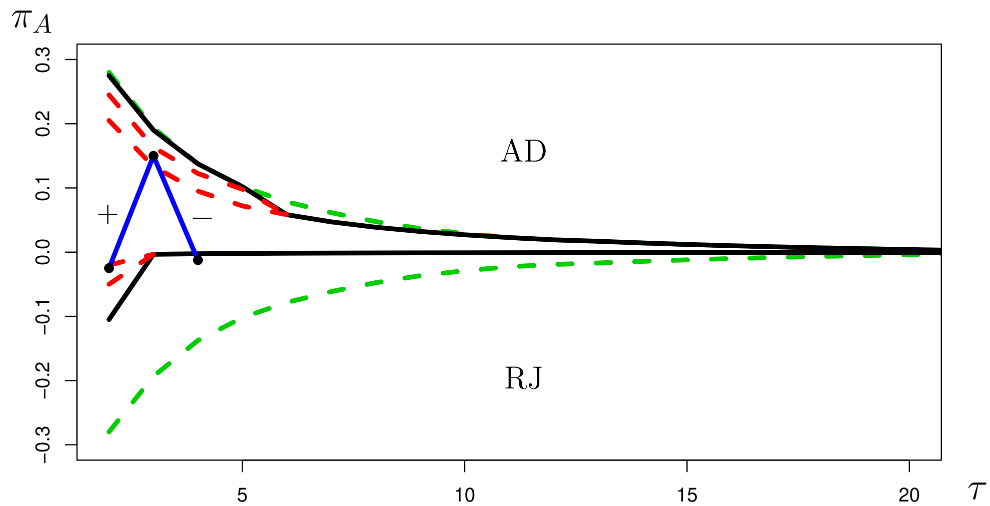

FIGURE 4.6: Example 6 and 7: The unraveling effect for $\theta = 5/4$

Note that Example 6 and Example 7 show that the anticipation of partner's decisions in subsequent periods could trigger unraveling effect, leading to a sequence of anticipated premature decisions at earlier periods. This unraveling effect is illustrated by the three points connected by a wedge "$\bigwedge$" lines in Figure 4.6. As discussed in Example 6, if the partnership belief is represented by $\alpha = 1.95$ and $\tau = 4$ (corresponding to the point at the bottom right of "$\bigwedge$" in Figure 4.6), A would be forced to make a premature rejection decision for the partnership because B would deny a request for information acquisition. Consequently, if this belief is reached after receiving a negative signal ($-$), i.e., if the partnership belief were $\alpha = 1.95$ with $\tau = 3$ (corresponding to the point at the top of "$\bigwedge$" in Figure 4.6), it would have been optimal for A to prematurely adopt the technology for the partnership at that point. Further, as discussed in Example 7, anticipating this premature adoption decision by A with $\alpha = 1.95$ and $\tau = 3$, would force B to deny a request for information acquisition if the partnership belief were $\alpha = 0.95$ with $\tau = 2$ (corresponding to the point at the bottom left of "$\bigwedge$" in Figure 4.6; note that receiving a positive signal ($+$) at that point would update partnership belief to $\alpha = 1.95$ and $\tau = 3$). Consequently, this unraveling would force A to make a terminal decision and thus result in the premature rejection decision with the partnership belief represented by $\alpha = 0.95$ with $\tau = 2$.

Note that in Example 6, A's premature adoption decision is anticipatory of B's subsequent denials, so A voluntarily makes a premature decision at that time (i.e., A herself makes a terminal premature technology adoption, instead of B potentially "forcing" her to do so in a subsequent period). In contrast, in Example 7, A's premature rejection decision is involuntary since B's denial of information request forces A to make a terminal premature technology adoption. However, optimal policy for the partnership may also include voluntary premature rejection and involuntary premature adoption decisions. In Example 8 and Example 9 below, we describe and discuss such premature decisions, as well as the corresponding unraveling effect.

Example 8. *Consider a partnership with* $\theta = 4/5$*. Let* $\alpha = 1.55$ *and* $\tau = 4$*. First note that A's SDM optimal policy is to acquire information, as* $\Delta_A(1, 1.55, 4) = 0.00435 > 0 > -0.112 = \pi_A(1, 1.55, 4)$*. Also note that if A were to make a request for the partnership to acquire additional information, B would approve it because* $\Delta_B(0.8, 1.55, 4) = 0.0433 > 0$*. However, it is not optimal for A to request infor-*

mation acquisition, as $\Delta_A(0.8, 1.55, 4) = -0.00612 < 0$. *This is due to A's continuation value being larger in the SDM setting than in the partnership setting, i.e.,* $\Delta_A(1, 1.55, 4) = 0.00435 > -0.00612 = \Delta_A(0.8, 1.55, 4)$. *Specifically, if A were to acquire information and a positive signal were received (resulting in unit increase of* $\alpha = 1.55 + 1 = 2.55$ *and unit increase of* $\tau = 4 + 1 = 5$*), A would then want to acquire an additional signal, as* $\Delta_A(0.8, 2.55, 5) = 0.0368 > 0.01 = \pi_A(0.8, 2.55, 5)$. *However, should A make this request, B would deny it, as* $\Delta_B(0.8, 2.55, 5) = 0.112 < 0.137 = \pi_B(0.8, 2.55, 5)$. *(On the other hand, if a negative signal were received, A would reject the technology.) Thus, B's denial of any subsequent information acquisition requests is accounted for in* $\Delta_A(0.8, 1.55, 4)$. *Because A will not be able to acquire subsequent information, it is optimal for A not to acquire information now, and instead prematurely reject the technology for the partnership.*

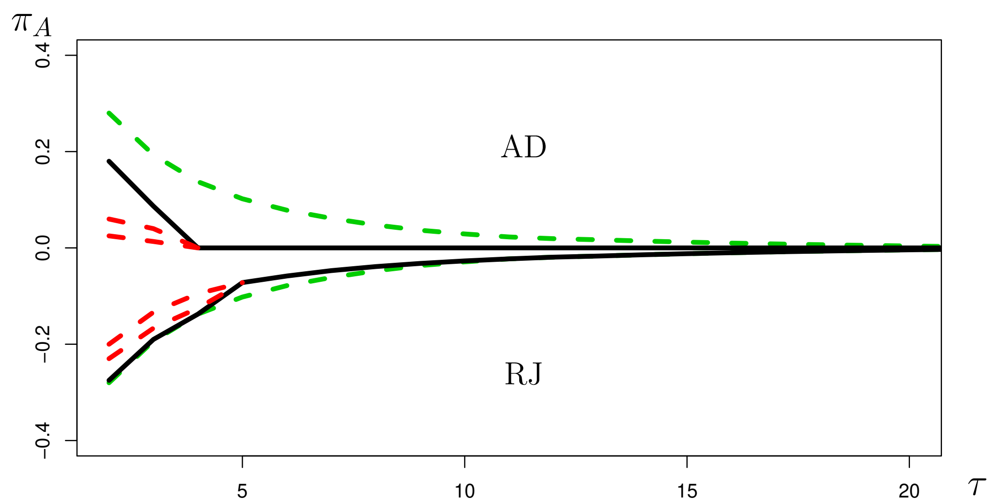

FIGURE 4.7: Optimal policy regions for $\theta = 4/5$

Figure 4.8 shows A's values associated with terminal decision to reject (RJ) and the decision to acquire additional information assuming B would approve that par-

ticular request (CT), as a function of α around the premature rejection region given $\tau = 4$. (This corresponds to part of the vertical slice at $\tau = 4$ in Figure 4.7, after converting α to A's expected value of the technology π_A, as discussed at the beginning of Section 4.3.2.) Note that A's value associated with acquiring additional information has discontinuity at $\alpha = 1.49$. For $\alpha < 1.49$, B would approve a subsequent request for additional information acquisition. For $\alpha > 1.49$, B would deny any subsequent requests, thereby reducing A's continuation value. This leads to the premature rejection region marked by the two dashed vertical lines.

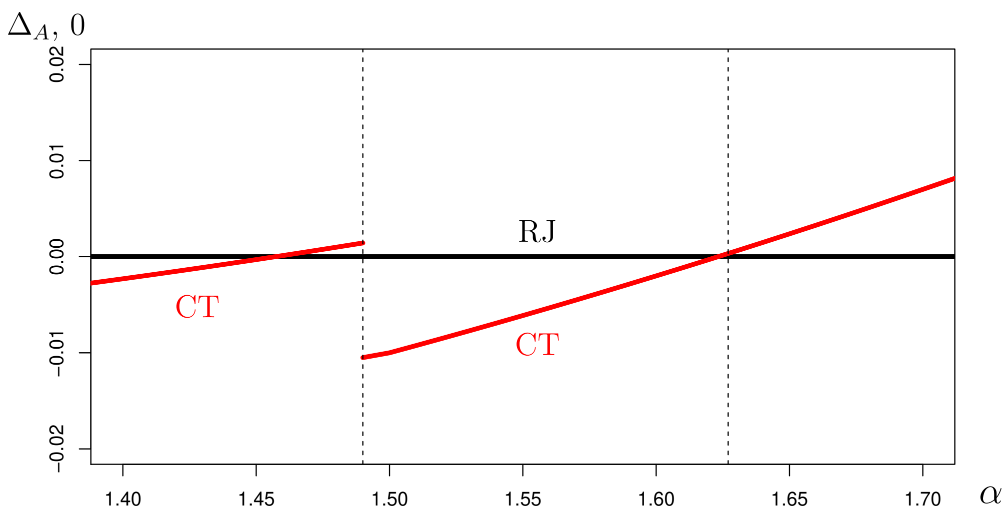

FIGURE 4.8: Premature rejection: A's values of RJ and CT in α for $\theta = 4/5$ and $\tau = 4$

□

We next illustrate emergence of premature adoption in the optimal policy for the same partnership.

Example 9. *Consider again the optimal policy for the same partnership in Example 8, but now let $\alpha = 1.55$ and $\tau = 3$. First note that A's SDM optimal policy is* *to acquire information, as* $\Delta_A(1, 1.55, 3) = 0.0631 > 0.0167 = \pi_A(1, 1.55, 3)$*. Also note that A would prefer for the partnership to acquire information rather than adopt the technology, as* $\Delta_A(0.8, 1.55, 3) = 0.061 > 0.0167 = \pi_A(0.8, 1.55, 3)$*. However, if A were to request information acquisition, B would deny it as* $\Delta_B(0.8, 1.55, 3) = 0.143 < 0.146 = \pi_B(0.8, 1.55, 3)$*. Note that B's denial of A's request is accounted for a possible A's premature rejection decision which was described and discussed in Example 8; if B were to approve A's request and if a negative signal were received, this would result in no change of* $\alpha = 1.55$ *and an unit increase of* $\tau = 3 + 1 = 4$*, which is the setting of Example 8. Since it is optimal for B to deny A's request at* $\tau = 3$*, it follows that A's optimal decision for the partnership is to prematurely adopt the technology.*

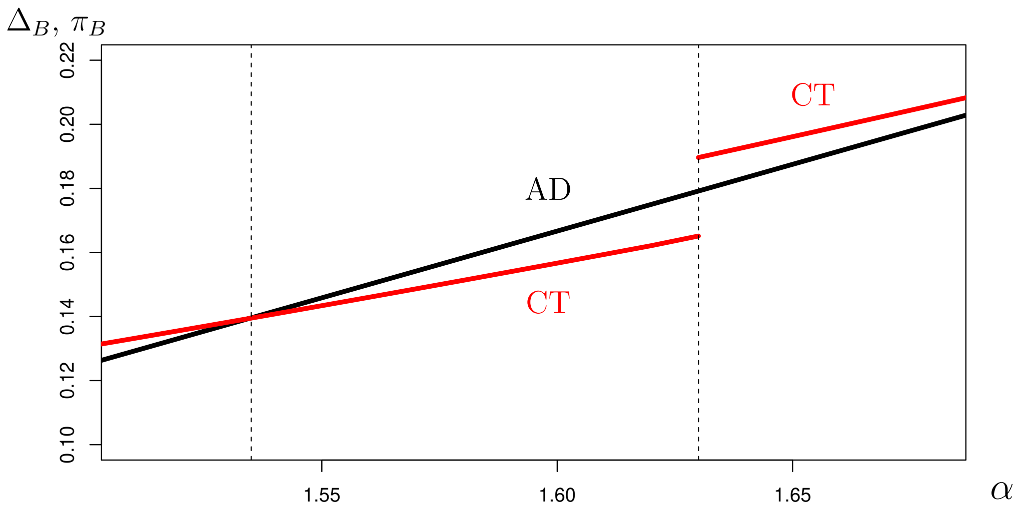

FIGURE 4.9: Premature adoption: B's values of AD and CT in α for $\theta = 4/5$ and $\tau = 3$

Figure 4.9 shows B's values associated with the terminal decision to adopt the technology (AD), which is A's optimal terminal decision, and with the decision to acquire additional information provided that A would request it, as a function of α

around the premature adoption region given $\tau = 3$. (Figure 4.9 corresponds to part of the vertical slice at $\tau = 3$ in Figure 4.7, analogous to description of Figure 4.8 in Example 8.) Note that B's value associated with acquiring additional information has discontinuity at $\alpha = 1.63$. Similar to the discussion in Example 8, this discontinuity is due to the anticipated A's premature rejection decision in the case of a negative signal realization, thereby reducing B continuation value. This in turn leads to A prematurely adopting the technology for values of α that fall between the two dashed vertical lines. □

4.3.3 Non-equal Costs

The results presented in this section are derived under assumption (4.12), i.e., that partners have equal costs. This assumption simplified the analysis, derivation of results, and discussion of the optimal policy structure. We now establish that (4.12) is not necessary, and that the optimal policy for the partnership with

$$\gamma = K_A/K_B = c_A/c_B \neq 1 \tag{4.32}$$

need not be monotonic.

Proposition 19. *There exists $\gamma \neq 1$ and $\theta \neq \gamma$ such that the optimal policy for the partnership is not monotonic.*

Proof. We first analyze the three-period setting. Similar as in the proof of Lemma 10, let $\tau = 1$ in the first period, and consider the case in which $\tau/2 < \alpha < \tau$ and $\alpha/(\tau + 1) < \tau/2$. Again, note that, if $\tau/2 < \alpha < \tau$, it is optimal for A to adopt the technology in the second period if receiving a positive signal in the first period. Thus, we only need to consider A's decision in the second period if receiving a negative signal in the first period. With a general cost ratio γ, we now have four state variables, i.e., γ, θ, α and τ. First, we need to solve for the following three conditions, satisfying which *i*) B would approve A's request in the first period but deny A's request in the second period if receiving a negative signal in the first period; ii) A would adopt the technology in the first period.

$$\Delta_B(\gamma,\theta,\alpha,1) = \frac{-0.01}{\gamma} + \alpha(\frac{\alpha+1}{2\theta} - \frac{0.5}{\gamma}) > \frac{\alpha}{\theta} - \frac{0.5}{\gamma} = \pi_B(\gamma,\theta,\alpha,1), \tag{4.33}$$

$$\Delta_B(\gamma,\theta,\alpha,2) = \frac{-0.01}{\gamma} + \frac{\alpha}{2}(\frac{\alpha+1}{3\theta} - \frac{0.5}{\gamma}) < 0, \tag{4.34}$$

and

$$\Delta_A(\gamma,\theta,\alpha,1) = \frac{-0.01}{\gamma} + \alpha(\frac{\alpha+1}{2} - \frac{0.5}{\gamma}) < \alpha - \frac{0.5}{\gamma} = \pi_A(\gamma,\theta,\alpha,1). \tag{4.35}$$

Solving the inequalities, we have the following sets of conditions:

1) $0 < \gamma \leqslant 0.815217$, $\theta > 1$,

and $0.858579 < \alpha < (0.5(\gamma+\theta))/\gamma - 0.1\sqrt{(25\gamma^2 - 48\gamma\theta + 25\theta^2)/\gamma^2}$;

2) $0.815217 < \gamma < 0.844669$, $1 < \theta \leqslant 1.22667\gamma$, and $0.858579 < \alpha < (0.25(-2\gamma + 3\theta))/\gamma + 0.05\sqrt{(100\gamma^2 - 276\gamma\theta + 225\theta^2)/\gamma^2}$, or $\theta > 1.22667\gamma$, and $0.858579 < \alpha < (0.5(\gamma+\theta))/\gamma - 0.1\sqrt{(25\gamma^2 - 48\gamma\theta + 25\theta^2)/\gamma^2}$;

3) $\gamma > 0.844669$, $1.18\gamma < \theta \leqslant 1.22667\gamma$ and $0.858579 < \alpha < (0.25(-2\gamma + 3\theta))/\gamma + 0.05\sqrt{(100\gamma^2 - 276\gamma\theta + 225\theta^2)/\gamma^2}$, or $\theta > 1.22667\gamma$, and $0.858579 < \alpha < (0.5(\gamma + \theta))/\gamma - 0.1\sqrt{(25\gamma^2 - 48\gamma\theta + 25\theta^2)/\gamma^2}$.

Next, we need to solve for the following four conditions, satisfying which i) B would approve A's request in both the first and the second period; ii) A would request information acquisition in both the first period and the second period.

$$\Delta_B(\gamma,\theta,\alpha,1) = \frac{-0.01}{\gamma} + \alpha(\frac{\alpha+1}{2\theta} - \frac{0.5}{\gamma}) + (1-\alpha)(\frac{-0.01}{\gamma} + \frac{\alpha}{2}(\frac{\alpha+1}{3\theta} - \frac{0.5}{\gamma})) > \frac{\alpha}{\theta} - \frac{0.5}{\gamma}, \tag{4.36}$$

$$\Delta_B(\gamma,\theta,\alpha,2) = \frac{-0.01}{\gamma} + \frac{\alpha}{2}(\frac{\alpha+1}{3\theta} - \frac{0.5}{\gamma}) > 0, \tag{4.37}$$

$$\Delta_A(\gamma,\theta,\alpha,1) = -0.01+\alpha(\frac{\alpha+1}{2}-0.5)+(1-\alpha)(-0.01+\frac{\alpha}{2}(\frac{\alpha+1}{3}-0.5)) > \alpha-0.5 \tag{4.38}$$

and

$$\Delta_A(\gamma,\theta,\alpha,2) = -0.01+\frac{\alpha}{2}(\frac{\alpha+1}{3}-0.5) > 0. \tag{4.39}$$

Solving the inequalities, we have the following sets of conditions:

1) $0.824561 < \gamma \leqslant 1$, $1 < \theta < 1.21277\gamma$,

and $(0.25(-2\gamma+3\theta))/\gamma + 0.05\sqrt{(100\gamma^2-276\gamma\theta+225\theta^2)/\gamma^2} < \alpha < 0.9$;

2) $1 < \gamma \leqslant 2.25$, $1 < \theta < \gamma$,

and $0.6 < \alpha < (0.25(2\gamma+3\theta))/\gamma - 0.05\sqrt{(100\gamma^2-276\gamma\theta+225\theta^2)/\gamma^2}$, or $\gamma < \theta < 1.21277\gamma$, and $(0.25(-2\gamma+3\theta))/\gamma + 0.05\sqrt{(100\gamma^2-276\gamma\theta+225\theta^2)/\gamma^2} < \alpha < 0.9$;

3) $\gamma > 2.25$, $0.444444\gamma < \theta < \gamma$

and $0.6 < \alpha < (0.25(2\gamma+3\theta))/\gamma - 0.05\sqrt{(100\gamma^2-276\gamma\theta+225\theta^2)/\gamma^2}$, or $\gamma < \theta < 1.21277$, and $(0.25(-2\gamma+3\theta))/\gamma + 0.05\sqrt{(100\gamma^2-276\gamma\theta+225\theta^2)/\gamma^2} < \alpha < 0.9$.

Finally, we need to solve for the following four conditions, satisfying which *i*) B would approve A's request in both the first and the second period; *ii*) A would adopt the technology in the first period but request information acquisition in the second period.

$$\Delta_B(\gamma,\theta,\alpha,1) = \frac{-0.01}{\gamma}+\alpha(\frac{\alpha+1}{2\theta}-\frac{0.5}{\gamma})+(1-\alpha)(\frac{-0.01}{\gamma}+\frac{\alpha}{2}(\frac{\alpha+1}{3\theta}-\frac{0.5}{\gamma})) > \frac{\alpha}{\theta}-\frac{0.5}{\gamma}, \tag{4.40}$$

$$\Delta_B(\gamma,\theta,\alpha,2) = \frac{-0.01}{\gamma}+\frac{\alpha}{2}(\frac{\alpha+1}{3\theta}-\frac{0.5}{\gamma}) > 0, \tag{4.41}$$

$$\Delta_A(\gamma,\theta,\alpha,1) = -0.01+\alpha(\frac{\alpha+1}{2}-0.5)+(1-\alpha)(-0.01+\frac{\alpha}{2}(\frac{\alpha+1}{3}-0.5)) < \alpha-0.5, \tag{4.42}$$

and

$$\Delta_A(\gamma,\theta,\alpha,2) = -0.01+\frac{\alpha}{2}(\frac{\alpha+1}{3}-0.5) > 0. \tag{4.43}$$

Solving the inequalities, we have the following sets of conditions:

1) $0.815217 < \gamma \leqslant 0.824561$, $1 < \theta < 1.22667\gamma$,

and $(0.25(-2\gamma + 3\theta))/\gamma + 0.05\sqrt{(100\gamma^2 - 276\gamma\theta + 225\theta^2)/\gamma^2} < \alpha < (0.25(2\gamma + 3\theta))/\gamma - 0.05\sqrt{(100\gamma^2 - 276\gamma\theta + 225\theta^2)/\gamma^2}$;

2) $0.824561 < \gamma \leqslant 1$, $1 < \theta \leqslant 1.21277\gamma$, and $0.9 < \alpha < (0.25(2\gamma + 3\theta))/\gamma - 0.05\sqrt{(100\gamma^2 - 276\gamma\theta + 225\theta^2)/\gamma^2}$, or $1.21277\gamma < \theta < 1.22667\gamma$, and $(0.25(-2\gamma + 3\theta))/\gamma + 0.05\sqrt{(100\gamma^2 - 276\gamma\theta + 225\theta^2)/\gamma^2} < \alpha < (0.25(2\gamma + 3\theta))/\gamma$;

3) $\gamma > 1$, $\gamma < \theta \leqslant 1.21277\gamma$

and $0.9 < \alpha < (0.25(2\gamma + 3\theta))/\gamma - 0.05\sqrt{(100\gamma^2 - 276\gamma\theta + 225\theta^2)/\gamma^2}$,

or $1.21277\gamma < \theta < 1.22667\gamma$,

and $(0.25(-2\gamma + 3\theta))/\gamma + 0.05\sqrt{(100\gamma^2 - 276\gamma\theta + 225\theta^2)/\gamma^2} < \alpha < (0.25(2\gamma + 3\theta))/\gamma - 0.05\sqrt{(100\gamma^2 - 276\gamma\theta + 225\theta^2)/\gamma^2}$.

Combining the all ranges in γ and θ, there exist $\underline{\gamma}$ and $\bar{\gamma}$, $\underline{\theta}$ and $\bar{\theta}$ such that, when γ and θ fall in between the respective thresholds, A's optimal decision is to adopt the technology, if $0.858579 < \alpha < (0.25(-2\gamma+3\theta))/\gamma+0.05\sqrt{(100\gamma^2 - 276\gamma\theta + 225\theta^2)/\gamma^2}$ and $0.9 < \alpha < (0.25(2\gamma + 3\theta))/\gamma - 0.05\sqrt{(100\gamma^2 - 276\gamma\theta + 225\theta^2)/\gamma^2}$. However, A's optimal decision in between the two adoption regions, i.e., $(0.25(-2\gamma + 3\theta))/\gamma + 0.05\sqrt{(100\gamma^2 - 276\gamma\theta + 225\theta^2)/\gamma^2} < \alpha < 0.9$, is to continue gather more information.

Next, we analyze the general infinite-period setting. Consider the case in which $\gamma = 4/5$, $\theta = 5/4$ and $\tau = 3$.

For $\alpha = 1.8$, B's optimal decision is to approve A's request, and A's optimal decision is to request, as

$$\Delta_A(0.8, 1.25, 1.8, 3) = 0.11 > 0.1 = \pi_A(0.8, 1.25, 1.8, 3), \tag{4.44}$$

and

$$\Delta_B(0.8, 1.25, 1.8, 3) = -0.0515 > -0.145 = \pi_B(0.8, 1.25, 1.8, 3). \tag{4.45}$$

For $\alpha = 1.95$, B's optimal decision is to approve A's request, but A's optimal decision is to adopt the technology, as

$$\Delta_A(0.8, 1.25, 1.95, 3) = 0.144 < 0.15 = \pi_A(0.8, 1.25, 1.95, 3), \tag{4.46}$$

and

$$\Delta_B(0.8, 1.25, 1.95, 3) = -0.0352 > -0.105 = \pi_B(0.8, 1.25, 1.95, 3). \tag{4.47}$$

For $\alpha = 2$, B's optimal decision is to approve A's request, and A's optimal decision is to request, as

$$\Delta_A(0.8, 1.25, 2, 3) = 0.17 > 0.167 = \pi_A(0.8, 1.25, 2, 3), \tag{4.48}$$

and

$$\Delta_B(0.8, 1.25, 2, 3) = -0.051 > -0.0917 = \pi_B(0.8, 1.25, 2, 3). \tag{4.49}$$

For $\alpha = 2.5$, B's optimal decision is to deny A's request, and A's optimal decision is to adopt the technology, as

$$\Delta_A(0.8, 1.25, 2.5, 3) = 0.324 < 0.333 = \pi_A(0.8, 1.25, 2.5, 3), \tag{4.50}$$

and

$$\Delta_B(0.8, 1.25, 2.5, 3) = -0.0354 < 0.0417 = \pi_B(0.8, 1.25, 2.5, 3). \tag{4.51}$$

This completes the proof. □

Thus, all results in this section readily extend even with (4.32). The proof of Proposition 19, similar to Proposition 17, establishes that the optimal policy for partnerships with $\gamma \neq 1$ is generically non-monotonic in the sense that there is a range of parameters γ and θ that yield a non-monotonic optimal policy for the partnership.

Further note that, with $\gamma \neq 1$, we can have partners having equal revenues, $\theta = 1$, and still have the non-monotonic optimal policy for the partnership. In fact, any difference between the partners' revenues and costs, i.e., $\theta \neq \gamma$ generically yields a non-monotonic optimal policy for the partnership. (Note, however, that proportional revenues and costs $\theta = \gamma$ reduces the optimal policy for the partnership to an SDM policy, as established by Proposition 15.). Proposition 16 suggests that differences in information acquisition costs c_A and c_B are not impacting the structure of the optimal policy in the sense that the optimal policy for the partnership coincides with SDM policy of one of the partners. Hence, it is the difference between one-time revenues from the technology, P_A and P_B, and one-time technology setup costs K_A and K_B, that results in non-monotonic optimal policy for the partnership that is fundamentally different from and structurally richer than SDM policies.

4.4 Concluding Remarks

We study a classical technology adoption problem (McCardle, 1985), but instead of a single risk-neutral decision-maker, we focus on the optimal policy for the partnership. Specifically, a risk-neutral decision-maker and her risk-neutral partner have potentially different values for the technology, and incur potentially different per-signal information acquisition and one-time technology setup costs. Additionally, decision-maker is in charge of making a terminal technology adoption/rejection decision for the partnership, but requires her partner's approval for any information acquisition. Hence, the partner has a passive role and a minimal oversight over the partnership's technology adoption decision-making process. Nevertheless, we establish that the presence of such partner has a profound impact on the structure of the optimal technology adoption policy for the partnership.

Unlike the SDM policy which is characterized by two thresholds that prescribe when to reject the technology, acquire information, or adopt the technology, the optimal policy for the partnership has a more complex structure which partitions the state space into non-contiguous regions corresponding to these three optimal decisions. Moreover, the optimal policy for the partnership may not be monotonic in the partnership's belief about the probability of technology success. Mathematically, these properties of the optimal policy for the partnership are due to non-convexity and discontinuity of the associated coupled optimization problem, indicating that finding a closed-form characterization might be elusive.

Note that our model utilizes binary signals, making analysis tractable. However, the dynamic decision problem formulation readily extends to more complex signal structures. While replicating our analysis with a richer signal structure might be challenging and potentially intractable, the fact that the optimal policy for the partnership is structurally different from any SDM policy would likely remain to hold with richer signal structures, since the main driver behind this result is not the signal structure but the difference in the objectives and decision-making powers of the two partners.

Finally, our findings suggest that there is a non-trivial impact on the optimal policy for complex decision problems, when decision-making responsibilities are assigned to multiple parties with different objectives. The exact allocation of decision-making responsibilities is likely to be context dependent, but whenever decision problems of two parties cannot be decoupled, as is the case in this chapter, decisions of one party will likely affect downstream decisions of the other party. This, in turn, could yield to anticipatory decisions and trigger unraveling in the form of a cascading sequence of premature decisions, just as we describe in the context of the optimal technology adoption and information acquisition for the partnership.

5

Conclusions

This dissertation studies three managerial problems: understanding and shaping user behavior in ride-hailing; managing innovation spillover in sourcing; and technology adoption and information acquisition in a partnership.

In Chapter 2, we study rider behavior and driver preferences and their impacts on the performance of ride-hailing platforms. Specifically, we develop an evolutionary game-theory model to study how rider behavior and driver preferences evolve under a rating system and characterize the asymptotic states of the system of a ride-hailing platform. Given the characterization, we show a ride-hailing platform could use operational tools such as price and wage adjustments to improve the performance of the platform and its long-run stability and sustainability. In addition, we establish that the platform could utilize a matching scheme that prioritizes high-rating riders under supply shortage to steer the system towards the socially optimal state.

In Chapter 3, we study the strategic sourcing decision of an innovator facing a competitor-supplier and a non-competitor-supplier, in the presence of innovation spillover risks. The innovation has an ex-ante uncertain value and could potentially be adopted by the competitor-supplier. We establish that the innovator's optimal strategic sourcing decision involves making the trade-off between managing innovation spillover risk and (not-) securing market-leadership position (captured by timing in either Cournot or Stackelberg competition). Furthermore, we show that the exact nature of this tradeoff depends on the structure of uncertainty in the product value that innovation brings, i.e., whether innovation has a downside risk.

Finally, in Chapter 4, we study the optimal technology adoption and information acquisition decision of a partnership facing a new technology that has an ex-ante uncertain value. By analyzing our dynamic model, we find that the optimal decisions for a partnership could be significantly different from those in the classical single decision-maker setting. In particular, we establish that the presence of a partner could trigger an unraveling effect that leads to a series of premature adoption and rejection decisions. Moreover, due to such unraveling effect, the structure of the optimal policy may no longer be monotonic in the belief of the success probability of the technology.

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Biography

Yunke Mai joined the Fuqua School of Business, Duke University as a Ph.D. student in Decision Sciences in August, 2013. Prior to joining Duke, he received his B.S. in Mathematics from Pennsylvania State University.