ORDER OF ENTRY ADVANTAGES IN NATURAL RESOURCES INDUSTRIES

ABSTRACT

This paper expands order of entry advantage theory by applying it to natural resources industries. In these industries, firms can take advantage of the oscillation of relative prices to strategically switch between serving different markets. Using a game theory decision-making framework, we model the entry timing of two cohorts of competitors: a crowd group, which makes the entry decision based on current market prices, and an anti-crowd group, which follows a countercyclical strategy by forecasting future prices using information related to competitors' movements. Through a mathematical simulation, we determine that the first-mover advantage captured by the anti-crowd group increases with the number of competitors in the industry and/or their price sensitivity, and decreases with the time required to switch between markets. These results do not depend on the existence of traditional competitive isolating mechanisms.

Keywords: Competitive Dynamics, Game Theory, Mathematical Simulation, Natural Resources Industries, Order of Entry Advantage.

Scholars in the strategic management field have long been concerned with the question of whether firms can create competitive advantages by strategically timing their entry into new markets (Lieberman & Montgomery, 2013; Makadok, 1998; Zachary, Gianiodis, Payne, & Markman, 2014). A significant body of research agrees that order of entry competitive advantage emerges as the result of the existence of competitive isolating mechanisms, which are contingent on contextual conditions (Lieberman & Montgomery, 1988; Mueller, 1997; Suárez & Lanzolla, 2007; Zachary et al., 2014). However, it is still unclear how and under what conditions order of entry matters (Zachary et al., 2014), since the theory has been unable to sort out conflicting empirical evidence and provide managers with coherent guidelines (Suárez & Lanzolla, 2007).

Theory on order of entry advantages has to resolve two fundamental challenges. First, new market emergence is a rare occurrence and context parameters are often too unique to allow meaningful comparisons across new markets (Klingebiel & Joseph, 2016; Lieberman & Montgomery, 2013). Second, order of entry advantage is a macro concept combining a variety of specific mechanisms; arguably, these should be studied individually (Lieberman & Montgomery, 2013). We explore these limitations in a particular context: natural resources industries. These cyclical industries are built around particular natural resources (e.g. agriculture, mining, oil) and face a highly competitive commodity market. In this context, firms can take advantage of the oscillation of relative prices to switch between serving different markets. Therefore, firms have multiple opportunities to enter and exit particular markets, allowing us to better understand the mechanisms leading to order of entry advantages. Our analysis is relevant not only from a theoretical standpoint, but also for the business community, since natural resources represent around one third of global exports, and national economic activity in most emerging economies and several developed countries depends heavily on natural resources industries.

We design an entry game (Cavagna, 1998; Challet & Zhang, 1998; Lo, Hui, & Johnson, 2000) in which a small fraction of competitors within an industry consistently aims to remain in the minority, entering underserved markets long before the prices in these markets reach their maximum values. As the game progresses, non-trivial cyclical fluctuations arise from competitors' collective decisions, which are generated by the dynamic formation of a crowd group, consisting of competitors using cyclical strategies, and an anti-crowd group, consisting of competitors using anticyclical strategies. The repeated recurrence of timing decisions in this setting makes it easier to study the nature of order of entry advantages (Klingebiel & Joseph, 2016).

To explore this unique competitive dynamic, we use game theory lenses to develop a mathematical simulation model that mimics the behavior of the market participants. We define two different groups of competitors that use contrasting strategies. The majority group ("the crowd") makes market entry decisions by analyzing current average prices; the minority group ("the anti-crowd") analyzes current prices but also forecasts future price levels by taking into account the number of competitors that are currently moving from one market to the other. Our work reveals that anti-crowd competitors can gain an order of entry advantage and capture abnormal returns under certain conditions: when (1) setup time decreases, (2) competitors' price sensitivity increases, and (3) the number of competitors increases.

Our research provides several contributions. First, we contribute to the order of entry literature by analyzing a situation with multiple opportunities to enter and exit the same markets, allowing us to develop fine-grained mechanisms of advantages. We also describe a particular approach for creating a competitive advantage that does not depend on competitive isolating mechanisms: decision-making based on competitors' behavior. Moreover, our focus on natural resources industries fills a gap in the strategy literature, where these industries have received limited attention to date and consequently represent a rich area for further enquiry (George, Schillebeeckx, & Liak, 2015). We also address recent calls to advance order of entry theory by examining the relationship between successive market entry, entry timing strategies and firm performance through by means of a parametrized model. Finally, we contribute by applying game theory to strategy.

The rest of the paper is organized as follows: we first identify the main environmental variables that enable entry order advantages in natural resources industries. We then propose a mathematical simulation model to represent the competitive dynamics of a market in which a certain number of competitors follows a price-countercyclical strategy, reporting results and advancing theoretical propositions. We conclude by discussing the study's implications as well as its limitations.

ANTECEDENTS AND THEORETICAL INSIGHTS

The entry order advantage literature explores the potential competitive advantages for pioneers – firms that enter an industry in its infancy – or early movers, who enter just after the industry takes off (Echambadi, Bayus, & Agarwal, 2008). The main risk for pioneers is entering too early due to product underdevelopment or a lack of consumer demand for the new product or service (Min, Kalwani, & Robinson, 2006). Moreover, while industry standards are still in flux, pioneers might become trapped in a product design that customers do not want (Min et al., 2006). On the other hand, the risk for early movers is entering the market too late to catch up with the pioneers if the initial product design is successful. The two approaches result in different levels of uncertainty and multiple interdependent decision options among competitors, leading to different strategic recommendations.

A fundamental element of the concept of entry order advantage is the interdependence of firms' decisions, which generates an opportunity window. The existence of an opportunity window for any given firm relates directly to the strategic moves of the rest of the competitors in an industry. The basic mechanism that allows early movers to build order of entry advantages is the path-dependent nature of isolating mechanisms. For example, if competitors can benefit from learning economies, early movers decrease unit costs in a cumulative fashion, giving late entrants a strong competitive disadvantage. The same rationale can be extended to network externalities. Firms that build a community of users (e.g., competitors in operating systems or competitors in e-commerce) achieve a cumulative advantage that is very difficult for late movers to reverse. The typical competitive dynamics in an industry generate a long-term decline in real prices due to increasing rivalry, which raises pressures on unit margins (Klepper, 1996, 1997). As real prices fall, the strength of the isolating mechanism increases, eventually forcing late entrants either to exit the industry or to occupy a niche position (Agarwal, Sarkar, & Echambadi, 2002; Suárez & Lanzolla, 2007).

For multiple industries this type of opportunity window opens just once in the entire industry life cycle, and those companies that miss it face severe competitive disadvantages. Environmental conditions might amplify or diminish the length of the opportunity window and the difficulty of entering into the industry during this period (Suárez & Lanzolla, 2007). The pace of market evolution and technology evolution can also affect the sustainability of the isolating mechanism. When they evolve gradually, the effect of isolating mechanisms will be the strongest; when environmental variables they are volatile (i.e., high-velocity environments), the effect of the isolating mechanism substantially decreases (Suárez & Lanzolla, 2007).

However, not every industry fits the main assumptions of this analysis: in natural resources industries, the product is usually a commodity with a minor or almost non-existent evolution along time, the markets are generally slow paced, and technology disruptions are scarce. Prices fluctuate in cycles, alternating between periods of high and low unit margins without following a clear long-term trend (Erten & Ocampo, 2013; Jacks, 2013). Moreover, while isolating mechanisms exist in several natural resources industries in the form of scale economies, several of these industries present high levels of atomization, sustaining hundreds or thousands of competitors for decades (e.g., agriculture). We ask the fundamental question: does order of entry advantage hold in this context? In particular, is it possible to observe an opportunity window that leads to a competitive advantage? If so, how do successful competitors handle such an opportunity window?

We take advantage of game theory to address these questions. Interdependence is a central theoretical theme of game theory, which makes this approach particularly suitable for our analysis (Camerer, 1991). We frame our analysis around the game of deciding to join one of two groups of competitors in an industry: the crowd group or the anti-crowd group (Cavagna, 1998; Challet & Zhang, 1998; Lo et al., 2000). An odd number N of competitors successively compete to join the anti-crowd group. We randomly assign several strategies to each agent at the beginning of the game, introducing some quenched disorder. As the game progresses, non-trivial fluctuations arise in competitors' collective decisions. These can be understood in terms of the dynamic formation of a crowd group, consisting of competitors using cyclical strategies, and an anti-crowd group, consisting of competitors using anticyclical strategies.

Anti-crowd competitors following an anticyclical strategy face a fundamental trade-off, sacrificing revenue in the short run for the opportunity to possibly earn higher revenue in the long run. However, the potential for higher revenue in the long run depends on the number of competitors that follow a cyclical strategy; that is, future revenue is contingent on other competitors' decisions and uncertain. Given this uncertainty, the majority of competitors – the crowd group – place a higher value on short-run revenue and choose to follow cyclical strategies. These two distinct decision-making strategies affect the order of entry into the market, which in turn determines cumulative performance. Anti-crowd competitors will seek to achieve order of entry advantages, entering a market when demand and prices are low. Crowd competitors, on the other hand, will wait until demand and prices rise before entering.

Like most analyses of order of entry advantage, this process is subject to various contingencies (Suárez & Lanzolla, 2007; Zachary et al., 2014). Given that order of entry advantage is a dynamic concept, it is best specified through interactions rather than direct effects (Lieberman & Montgomery, 2013). We focus on three important environmental enablers: technological conditions, environmental dynamism, and rivalry level, which are represented in our model, respectively, by the following measurable variables: the time required to switch between markets –setup time-, the competitors' price sensitivity and the number of competitors in the industry, respectively. Environmental dynamism is a fundamental factor in order of entry competition (Suárez & Lanzolla, 2007). For the game setting, this dynamism depends on the sensitivity that crowd and anti-crowd competitors have to shift among markets, since the aggregate market change will eventually result in supply and price alterations

(Erten & Ocampo, 2013; Jacks, 2013), influencing endogenously the commodity cycle. This pattern affects market munificence irrespective of the number of competitors, since cycles can be driven by external factors, such as behavior of financial commodity markets and macroeconomic growth (Cortazar, Kovacevic, & Schwartz, 2015; Mayer, 2009). We expect that the commodity cycle will impact the respective value of crowd and anti-crowd strategies.

Technological conditions can also affect the relative success of crowd and anti-crowd competitors, since, in this game, firms' market entry decisions are affected by the setup time required to start selling in the new market. Depending on the technological context, this setup time might be shorter, decreasing the duration of non-revenue periods.

Finally, competitive conditions –rivalry level-influence the level of market munificence, which in turn affects the value of order of entry strategies. In particular, when the value of being first stems from the opportunity to achieve higher margins in a crowded market, the number of competitors present in the industry catalyzes potential gains. Figure 1 describes the conceptual framework.

INSERT FIGURE 1 ABOUT HERE

Based on this framework, we specify variables and relationships to gain insight into competitive dynamics. The expected relationships are non-trivial given the endogenous nature of the price-quantity cycle. In our case, entrants change their strategy in response to market conditions, while market conditions shift as a result of entry decisions. For that reason, we develop a mathematical simulation model and, subsequently, build a theory offering several propositions.

MATHEMATICAL SIMULATION

Mathematical simulation is a useful methodological approach that helps in developing theory and bridging the gap between the main constructs and relationships and the empirical grounding of an analysis (Davis, Eisenhardt, & Bingham, 2007; Harrison, Lin, Carroll, & Carley, 2007; Simon, 1990). We are interested in how order of entry affects competitive advantage in a cyclical industry with no product differentiation or any type of competitive isolating mechanisms where prices are endogenous to competitors' investment decisions. Accordingly, we define a game that describes a system of multiple, interrelated agents in a path-dependent context under a cobweb process. The stochastic nature of these processes and interrelationships generates mathematical intractability that inhibits the possibility of finding an analytical solution. Therefore, we opt for a mathematical simulation – a powerful tool for advancing theory on complex behaviors and systems when derivations cannot be carried out due to mathematical intractability (Davis et al., 2007; Harrison et al., 2007). In addition, a mathematical simulation is appropriate for analyzing competitive dynamics when the market is conceived as an open complex system and the economic agents—i.e., individual firms—are interrelated with each other in that system (Dopfer, 2004).

Computer simulations permit us to capture greater variance as they account for large periods of the commodity cycle. In this vein, adequate tools can include the heterogeneous composition of strategic decisions, the possibility of multilevel feedback effects or interactions and a realistic representation of dynamic processes in an industry's history. Simulations also allow to formulate powerful predictions for further empirical testing and to test boundary conditions for prior theorizing (Pyka & Fagiolo, 2007).

We generate an agent-based stochastic model with a discrete time design. We keep the model design straightforward, following the rule that the simpler the model, the easier it is to gain insight into the causal processes at work (Harrison et al., 2007; Raghu, Sen, & Rao, 2003; Simon, 1990). We describe the mathematical structure of the model below.

Market. The model simulates a standard cobweb situation with *N* competitors that are price takers in two markets (i) for two undifferentiated products A and B. Each market faces a linear downward demand function $P_{it} = D(Q_{it})$. For simplicity's sake, both demand functions have the same shape parameters. The basic model starts with the *N* competitors distributed between both markets. Some of them are already in the process of switching from A to B (S_{AB}) and others are switching from B to A (S_{BA}). The market and the firms have no storage capability, and production level is zero when a competitor is in the process of switching from one market to the other. Therefore, the resulting price only depends on the quantity supplied by A and B producers.

Production Process. Firms own an asset capable of generating two different products A and B. However, this asset cannot produce both products simultaneously, forcing decision makers to choose one of the two. This situation is typical of commodity industries where land is the primary asset, such as agricultural products, wine, fruits, cattle and milk production. Firms have a given productivity. The asset determines the production capacity, which remains fixed along the simulation. All of the producers have the same size and productivity, variables that remain unchanged during the complete simulation period. In every period, all of the production is sold at market prices; none is carried over to the next period. In this setting, competitors are not able to build demand- or supply-side isolating mechanisms.

Firms have a setup time that determines the time to market when they decide to enter a new market. In agriculture, it is common to observe a time lag – based on biological constraints – between planting and reaching full production (McCullough, Huffaker, & Marsh, 2012; Nicholson & Stephenson, 2015). Oil and mining are other examples of commodity industries with setup times, due to the necessary time investment in discovery, exploration and development activities (Favero, Hashem Pesaran, & Sharma, 1994; Łucki & Szkutnik, 1990).

Profit. Agents can choose to produce and sell the current product or invest in a new product given price and production expectations. Producing and selling the current product – following the crowd strategy – will yield positive profit, whereas investing in the other product – following the anti-crowd strategy – will yield zero profit.

The model has a standard variable cost function. There are no learning economies and no scale economies, since all the producers are of the same size and produce at full capacity. The variable costs are yearly production costs and, for simplicity, remain the same for both types of product. While a producer is in the process of switching production from one product to the other, no revenue is generated and only maintenance costs are paid. The standard profit function for a firm *i* in time *t* is:

$$\pi_{it} = (P_{jt} - c_{jt})Q_{jt} \quad (1)$$

where c_{jt} represents the variable cost of product *j* at time *t*. The variable cost is the weighted average of each product unit cost. The value of Q_{jt} is 1 when the competitor is in production, and 0 otherwise. All competitors have the same amount of production when they are not switching from one product to another.

Performance. The existence of an order of entry competitive advantage should result in superior cumulative performance. Several elements affect performance: average prices, production setup time, and the total number of competitors. We compute the cumulative performance for each group of agents in the straightforward form of cumulative profit $CP_i = \sum_{t=1}^{T} \pi_{it}$. Since the model does not impose a limit to temporary losses, it implicitly assumes perfect financial markets that can finance transitory losses. We verify the amount of the cumulative losses to address the reasonableness of this assumption.

Decision Rule for Crowd and Anti-crowd Competitors. Decision-making is a fundamental antecedent in explaining order of entry advantages (Zachary et al., 2014). In the model, the main decision a producer has to make is whether to continue producing and selling the current product or switch to the alternative product, knowing that there exists a production setup time that imposes a lag between the decision to switch and the moment when the new product is sold.

The model defines two groups of competitors: crowd (*CR*) and anti-crowd (*AC*). Both groups of competitors have bounded rationality regarding the future but one group decides with a different set of information. *CR* competitors decide by looking at current prices while *AC* competitors look at current prices and at the current change rate of competitors from one product to the other. Therefore, $Q_{CRt} = f(P_{At}, P_{Bt})$ for *CR* competitors and $Q_{ACt} = f(P_{At}, P_{Bt}, S_{AB}, S_{BA})$ for *AC* competitors.

The decision to switch depends on the relative prices and the producers' sensitivity to change. A *CR* competitor that is producing A will remain there if

$$\frac{\lambda^{\left(\frac{P_{At}(Q_{At}) - P_{Bt}(Q_{Bt})}{P_{Bt}(Q_{Bt})}\right)}}{\lambda - 1} > RND \tag{2}$$

where λ is the change factor (the propensity to change products), and RND is a random number that follows a uniform distribution [0,1]. If the condition defined in (2) is not achieved, the *CR* competitor will begin switching production from A to B. An *AC* competitor producing A will continue doing so if

$$\frac{\lambda^{\left(\frac{P_{At}(Q_{At}+\Delta_{BA})-P_{Bt}(Q_{Bt}+\Delta_{AB})}{P_{Bt}(Q_{Bt}+\Delta_{AB})}\right)}}{\lambda-1} > RND \quad (3)$$

Where $\Delta_{BA} = \sum_1^n k_s Q_s$ indicates the number of producers that have already switched from B to A and will be entering into production after the next *n* years (*n* refers to the production setup time). If the condition defined in (3) is not achieved, the AC competitor will begin switching from A to B. The CR and AC competitors that switch production from product B to product A are parametrized in analogous ways, although the equations are not listed here.

The objective of anti-crowd competitors is to play anticyclically and begin producing when the prices of a product are highest, thus maximizing long-term revenues. Both types of competitors have the same level λ of sensitivity to change. Lower levels of λ are indicative of higher sensibility to change, i.e. competitors are more prone to change markets.

The switching process from one product to the other has restrictions given the cumulative profits of the individual producer. A producer that has cumulative losses cannot afford further losses and must wait until prices improve to switch markets. That is, firms that have several years of cumulative losses cannot afford to forgo immediate revenue to attempt to capture higher future revenue with the alternative product. Additionally, in an effort to replicate behavior observed in the real world, the maximum number of competitors switching products at the aggregate level is also limited, so even in extreme conditions, some producers do not change markets.

The initial number of *CR* and *AC* competitors is randomly assigned at the beginning of the simulation and remains constant. *AC* competitors are a minority. As the game evolves, we expect *AC* competitors to group into one product while the *CR* competitors remain evenly distributed between both products.

Parameters and Runs. We program the model in Java and solve it with Monte Carlo simulation. A fundamental decision in mathematical simulation models is to determine parameters to ensure a realistic grounding. Accordingly, we choose Australian grape farming as the reference model, focusing on red and white grape production. Table I reports the model parameters for the base case. The simulation runs for 100 periods with a warm up time of 10 periods, with 70 replications. Figure 2 outlines the model decision tree.

INSERT FIGURE 2 AND TABLE I ABOUT HERE

SIMULATION RESULTS AND PROPOSITIONS

The model renders a cobweb process that generates a system of cyclical prices, resulting in a continuous movement of producers from one product to the other. Figure 3 presents the price and production dynamics in each market. Prices behave in a cyclical fashion that is negatively correlated with the total market quantity. This market structure generates a price cycle like the one observed in commodities (Erten & Ocampo, 2013), which becomes a key process affecting performance (Nicholson & Stephenson, 2015). The price cycle oscillates between 2 and 8 years, similar to what has been observed for wine grapes, fruits, grains (Jacks, 2013), cattle (Mundlak & Huang, 1996), and the milk industry (Hunt & Kern, 2012). The aggregate market quantities mirror price behavior, given that boundary conditions imposed by the model fix the total demand and the number of competitors all along the simulation.

INSERT FIGURE 3 ABOUT HERE

It is worth noting that the price cycle lasts longer than the setup time, although this relationship between both variables varies across industries. For example, biological restrictions in the cattle industry impose a minimum two-year lag between gestation and the sale of a heifer in the market, but the price cycle lasts around 10 years in the US.

The Effect of an Anti-crowd Strategy on Order of Entry Sustainable Advantage.

The fundamental determinant of performance in natural resources industries is market timing, which eventually leads to an order of entry competitive advantage. The existence of a period between the decision to switch from one type of product to another and the moment of full production generates opportunities for arbitrage. The key feature of this competitive framework is the absence of competitive isolating mechanisms. Competitors gain an advantage from strategically timing market entry, but this advantage is temporary, until imitation pressures push prices downward. The basic trade-off anti-crowd players face is between certain short-term losses and uncertain long-term gains. Short-term losses result from the decision to stop producing and selling a higher-priced product during the transition period until the new product enters into full production. Long-term gains may eventually result from the higher prices the anti-crowd competitor can charge after beginning to produce the new product and before crowd competitors enter the market.

The determinant of market timing and, consequently, of competitive advantage, is the type of information competitors base their market entry decisions on – either prices or production and prices. Since crowd competitors look only at prices, they behave cyclically. Anti-crowd competitors, who also take into account other competitors' investments in the new product, tend to behave countercyclically. The endogeneity of the aggregate production cycle gives producers incentives to expand their sources of information. At the individual level, competitors cannot alter market prices, but when their decisions are aggregated, they generate supply changes at the industry level. The two distinct decision rules generate an intertemporal disequilibrium in the market.

Figure 4 reports the results of two cumulative profits simulations for the basic case, with just one differing parameter: the competitors' sensitivity to market price movements. Figure 4a depicts low sensitivity and Figure B shows high sensitivity. We observe that the anti-crowd strategy is not always successful. Depending on multiple factors, such as competitors' sensitivity to prices, setup time, the total number of competitors and the percentage of anti-crowd competitors present in the market, results will vary. In fact, in most cases, the crowd group's mean profit is higher than those of the anti-crowd group, as shown in Figure 4a. Even when the anti-crowd strategy outperforms the crowd strategy in the long run (Figure 4b), their short- and medium-term results are indistinguishable. Therefore, we argue that anti-crowd competitors can potentially achieve higher abnormal returns than crowd competitors, but any such outperformance is contingent on several factors.

INSERT FIGURE 4 ABOUT HERE

The potential for anti-crowd competitors to outperform their counterparts stems from their ability to detect an increase in the number of firms entering the more attractive market (i.e. the market with higher product prices). As the number of competitors increases, prices begin to decline. Beyond a certain threshold, anti-crowd competitors switch to the product with lower prices. They forgo revenue during a temporary setup period, but this loss is eventually compensated by higher revenues from the new market, which had been previously abandoned by the crowd. Therefore, under certain conditions, anti-crowd competitors outperform crowd competitors. Consequently, we propose that:

Proposition 1a: Firms following an anti-crowd strategy can achieve an order of entry competitive advantage when competing in cyclical industries.

Proposition 1b: Firms competing in cyclical industries can achieve order of entry advantages even in the absence of competitive isolating mechanisms.

We show the possibility of an anti-crowd strategy as a source of first-mover competitive advantage in the absence of isolating mechanisms. However, the conditions that allow such an advantage to develop remain loosely defined. Therefore, in order to fine-tune the mechanisms leading to order of entry advantages, we analyze the effect of three factors –setup time, competitors' price sensibility and the number of competitors in the industry- on anti-crowd performance.

Setup time affects price volatility: the longer it takes a producer to enter a market, the longer it will take for prices in that market to react. Once competitors reach their productive state, market prices will adjust downward. In various natural resources industries, this setup time reflects natural limitations, which have been identified as an endogenous source of market disequilibrium and price oscillation (McCullough et al., 2012).

Producers' price sensitivity also affects the price gap between markets. As price sensitivity surges, so does the switch rate between markets, producing a stampede effect that increases the price gap. The concept of price sensitivity captures the cognitive determinants of time-to-market – i.e. the propensity to behave countercyclically (Hamilton & Kastens, 2000).

Finally, the number of competitors affects price volatility and the price gap between markets: as more competitors interact in the market, more of them switch from one market to the other. Additionally, a higher number of competitors boosts the value and potential gains of an anti-crowd strategy, as the crowd competitors focus just on one product, increasing volatility and reducing prices in that market.

In order to better understand the mechanisms leading to order of entry competitive advantage, we isolate the effect of each factor in the subsequent sections.

The Effect of Technological Conditions.

A fundamental friction in many markets is the setup time between the decision to enter a market and the moment of full production. This situation is typical in most natural resources industries, ranging from petroleum to agriculture. A vineyard needs around three years to start producing quality grapes, and it can be up to another three years before the wines have aged properly and are ready for the marketplace. The setup time is similar for several fruits, such as apples and avocados. In mining, the production setup time ranges from 7 to 20 years. Because depending on the technological context setup time will vary, we use this variable as a proxy to measure technological conditions.

We explore to what extent changes in setup time enhance or decrease the value of an anti-crowd strategy. The setup time determines the number of periods of zero revenue. A jump in the setup time increases industry coordination problems: anti-crowd competitors face a higher opportunity cost of exiting the most profitable market, while crowd competitors face future longer periods of high prices. A drop in the setup time, given that anti-crowd competitors are in the minority, favors their strategy since they will be able to enjoy a first-mover advantage in future while minimizing losses stemming from the decision to switch markets. Additionally, since setup time affects crowd and anti-crowd competitors equally, a shorter setup time encourages a bandwagon effect, as crowd competitors switch markets faster and more frequently to benefit from higher prices. This increases market volatility and consequently, expands the opportunities for anti-crowd competitors to earn abnormal revenues.

Figure 5 shows the crossed impact of price sensitivity, setup time and total number of competitors on anti-crowd performance. Anti-crowd performance is measured relative to that of the crowd group; it is calculated as the profit difference between the two groups as a percentage of the average profit. The observed relationship among factors is nonlinear. The setup time ranges from 1 to 4 years; the competitors' price sensitivity, measured as ln(Change Factor), varies from 10 (low sensitivity, Change Factor=100) to -10 (high sensitivity, Change Factor=0.01); the total number of producers ranges from 2000 to 7700. In Figure 5b, we observe that setup time barely affects anti-crowd performance. However, a shorter setup time makes it possible for anti-crowd competitors to outperform the crowd group even in a context of lower volatility. From Figure 5c, we can observe that the anti-crowd performance is highest for short setup times in a competitive market (high number of competitors). In general, the effect of setup time is flatter and less significant than the effect of market competitiveness and competitors' price sensitivity.

INSERT FIGURE 5 ABOUT HERE

Therefore, we propose that:

Proposition 2a: The longer the setup time between the decision to enter a market and the first product sold, the lower the margins of both crowd and anti-crowd competitors.

Proposition 2b. The advantage of following an anti-crowd strategy increases as setup time decreases.

The Effect of Environmental Dynamism.

It is known that environmental dynamism influences order of entry advantages in industries with isolating mechanisms in place (Suárez & Lanzolla, 2007). We examine to what extent environmental dynamism affects order of entry advantages in the absence of isolating mechanisms. In our analysis, this dynamism depends on the competitors' propensity to switch markets, since the aggregate combination of market changes ultimately generates endogenous environmental instability in the form of supply and price cycles. This endogenous volatility is defined in the model as competitors' price sensitivity. Competitors differ in their price sensitivity, that is, in their willingness to switch markets when relative prices change. Lower sensitivity – competitors are less likely to switch markets- might reflect higher risk aversion, a more long-term orientation, or the expectation that the price cycle will last longer (i.e., the assumption that other competitors will react slowly to price changes).

Figure 3 shows the endogenous nature of cycles, with prices behaving in a cyclical and negatively correlated fashion. Low price sensitivity among competitors is associated with less extreme price oscillation. Aggregate production mirrors this behavior in an inverse manner. Figures 5a and 5b illustrate the effect of price sensitivity on the mean difference in profit between the anti-crowd and the crowd groups. When the change factor declines, price variability increases, which generates a positive effect on anti-crowd performance. Interestingly, not every change factor value allows for a window of opportunity for anti-crowd competitors. In fact, we observe that when ln(Change Factor) is greater than -5, the crowd group always outperforms the anti-crowd group, regardless of the value of the other factors. This occurs because, as the price sensitivity rises, so does the probability that the crowd competitors remain in or move to the market with the higher prices. As the cycle reverses and prices fall, crowd competitors react swiftly, intensifying the cycle amplitude. As the cycle's amplitude rises, so does the opportunity for anti-crowd competitors to get higher gains. Thus, we suggest that:

Proposition 3: The higher the sensitivity of competitors to changes in relative prices, the greater the advantage of following an anti-crowd strategy.

The Effect of Competitive Conditions.

Competitive conditions are a well-established contingency to order of entry advantages (Baum & Korn, 1999; Fuentelsaz, Gomez, & Polo, 2002; Zachary et al., 2014). However, not all theories make the same predictions when entering into highly competitive markets. For instance, oligopoly theory establishes that markets with low rivalry are not attractive for new entrants since the existing competitors can coordinate their actions to prevent entry (Sherer & Ross, 1990). Furthermore, a high level of rivalry can be indicative of a market with opportunities for high profits. On the other hand, the contestable markets theory does not recognize any significant effect of market concentration on firm performance. Finally, according to Mitchell, (1989), when rivalry levels are high, incumbents may react to new threats, reducing the profitability of new entrants. For industries with homogenous products, including natural resources industries, rivalry is inversely proportional to the number of competitors. In this context, we recognize two potential effects of the number of competitors on anti-crowd group performance. On one hand, when more competitors interact in the market, there is a higher likelihood of producers switching from one market to the other, diminishing the opportunity to follow a successful minority anti-crowd strategy. But at the same time, and assuming a generalized risk aversion that is asymmetric between the crowd and anti-crowd strategy populations, we expect the crowd group to expand, reducing market prices, increasing the price volatility, and thus, boosting potential gains for the anti-crowd group. In Figures 5a and 5c, we can observe that, as the number of competitors increases, the performance of the anti-crowd group improves. Nevertheless, this positive effect is limited to markets with high rivalry. In the base case simulation shown in Figure 5, it is only when the total number of producers is greater than 5000 that anti-crowd competitors have a window of opportunity to outperform crowd competitors. Below this number, crowd competitors perform better. Remarkably, a highly competitive market does not assure a successful anti-crowd strategy; the potential success of such a strategy also depends on the interrelated factors of price sensitivity and setup time.Thus, we argue that:

Proposition 4a: The greater the number of competitors in an industry with cost competition, no product differentiation, and no substitute products, the lower the advantage of following any strategy, crowd or anti-crowd.

Proposition 4b: As the number of competitors increases, so does the value of an anti-crowd strategy, since crowd competitors tend to focus on one product.

The Impact of the Anti-Crowd Group Size.

There is one more relevant element to consider: the percentage of anti-crowd competitors in the market. We do not classify this as a factor since one of the game's conditions specifies that anti-crowd competitors must remain in the minority, effectively limiting their number. However, we can ask: What is the maximum size of the anti-crowd group that still plausibly allows the competitors in this group to outperform the crowd? Figure 6 answers that question by depicting the sensitivity of anti-crowd performance to the percentage of anti-crowd competitors (relative to the total number of competitors) and the main contingency factors (price sensitivity, setup time and total number of producers).

INSERT FIGURE 6 ABOUT HERE

Of the three charts included in Figure 6, Figure 6b shows the least restrictive conditions. In other words, there is a wide range of possible values for the percentage of anti-crowd competitors that allows for a positive anti-crowd performance, independent of the setup time. Nonetheless, if the proportion of anti-crowd producers exceeds 50%, crowd competitors perform better. In Figure 6a, we observe that the anti-crowd strategy is only feasible when fewer than 15% of the competitors fall into the anti-crowd group and price sensitivity is high. We find a similar effect in Figure 6c: the anti-crowd strategy is only effective when fewer than 15% of competitors follow it.

Across all of the charts in Figure 6, potential gains for anti-crowd competitors vanish as the number of members in their group increases. There are two reasons for this: First, it is not possible to follow a countercyclical strategy if a substantial group of competitors is following the same strategy. Second, producers' aggregate decisions affect the commodity cycle, reducing prices and thus cutting into first movers' revenues. Accordingly, we propose that:

Proposition 5: As the number of anti-crowd competitors increases, the advantage of an anti-crowd strategy decreases.

DISCUSSION

We analyze the extent to which order of entry in cyclical industries without isolating mechanisms can generate a competitive advantage. Companies competing in natural resources industries under the aforementioned conditions face a fundamental trade-off between exploiting prevailing high prices for a particular product and making investments in order to exploit future high prices for an alternative product.

We propose an early mover advantage that is independent of traditional isolating mechanisms. Antecedents illustrate the existence of a one-time opportunity window that favors a sustainable competitive advantage for early entrants. In contrast, we highlight the existence of repeated opportunity windows based on the oscillation of commodity prices. Companies have the strategic option to use this oscillation to build a sustainable competitive advantage, which is related not to the existence of isolating mechanisms but to aggregate supply. Importantly, our framework is also applicable in cyclical industries where, even with isolating mechanisms in place, a strategic group in which all competitors enjoy a similar level of isolating mechanisms is clearly distinguishable.

The fact that the game generates order of entry competitive advantages in an industry without isolating mechanisms can help us understand competition not only in natural resources but also in differentiated product industries. To the extent that a differentiated product industry has high capital investments, lead time and potential for overinvestment, mastering timing of entry can also be a sustainable source of order of entry competitive advantage, even though prices may not oscillate as they do for commodities.

In our model, cycles are endogenously driven. However, the possibility of building order of entry advantages also exists for exogenously driven cycles, such as the business cycle. In fact, recent studies have started addressing the conditions under which the business cycle might alter order of entry advantages (García Sánchez, Mesquita, & Vassolo, 2014). For this to happen, there must be some isolating mechanisms in place. It is easy to think of potential isolating mechanisms in natural resources industries, mainly related to cost advantages (i.e. scale and learning economies). The existence of these mechanisms might reinforce order of entry advantages based on the decision-making process.

Our research formalizes the mechanisms behind anecdotal evidence suggesting that it may be possible to earn abnormal returns by determining the best times to start and stop producing a certain commodity product. In particular, several U.S. farmers producing milk sold their cows in early 2008, anticipating negative margins in 2009, and re-entered the market during 2010, earning abnormal returns (Nicholson & Stephenson, 2015). Interestingly, they planned their expansion during 2009, when prices of cows and equipment were low, entering into production at the end of 2010, when prices started to recover.

Firms face a tension between current revenue and cumulative revenue when they decide to switch markets based on a countercyclical approach. The critical decision is whether to use current prices as a proxy of future values. Since aggregate investment decisions might drop prices in the future, optimal current strategies request some degree of differentiation from competitors' decisions. Nevertheless, behaving countercyclically brings fundamental uncertainties, primarily centered around competitors' aggregate decisions, in a context where switching from one product to another has a substantial opportunity cost and a nontrivial setup time. However, simply following a countercyclical strategy analyzing competitors' investments does not necessarily lead to a sustainable competitive advantage. Such advantages exist primarily in competitive and volatile markets, where competitors are sensitive to price, and enjoy moderate setup times. Order of entry advantage also decreases as other firms enter the market. One of the conditions for the success of a countercyclical strategy is that the anti-crowd cohort must be small. As the number of members in the anti-crowd group increases, the potential gains vanish, since producers' aggregate decisions affect the cycle by reducing the price levels first movers can achieve.

Our study has implications that go beyond natural resources industries. We complement the literature on asset reconfiguration (Chakrabarti, Vidal, & Mitchell, 2011; Dierickx & Cool, 1989) where returns not only depend on factors such as efficiency or differentiation but also on the timing of buying or selling assets, introducing a new context: endogenously determined cycles.

Limitations

The set of assumptions in our basic model is a source of multiple limitations on the generalizability of our results. First, the type of competitive advantage described here is likely to lead to some degree of industry consolidation. However, the model does not allow for consolidation: companies that face losses remain in the industry. If we relax this assumption, we might observe increasing industry concentration, ultimately altering our findings.

Another limitation of our model is that we assume cycle regularity, when in reality the duration of cycles varies unpredictably. Anti-crowd competitors' performance can be seriously affected by such uncertainty, as their strategy is partially based on cycle forecasting.

Moreover, given that the value of an anti-crowd strategy depends on a minority of agents following such a strategy, future research should explore the factors that lead to learning in the crowd group and the mechanisms via which competitors might switch groups.

Finally, the cycle in our model is endogenously determined. However, natural resource prices depend also on factors exogenous to their industries, like the US interest rate or the financial markets. Therefore, future research should examine to what extent our findings hold as prices increasingly depend on exogenous factors.

CONCLUSION

Order of entry advantages have been a matter of intense analysis since Lieberman & Montgomery's (1988) seminal work. After several decades of research, the topic remains controversial, and it is still unclear how and under what conditions order of entry matters, both at the theoretical level and considering the empirical evidence (Zachary et al., 2014). We contribute to this debate by studying a previously unexplored setting: natural resources industries. Specifically, we develop a mathematical simulation model with a certain number of competitors following a price-countercyclical strategy ("the anti-crowd"). The success of this strategy depends on the existence of a sufficient number of competitors who follow a procyclical strategy ("the crowd"). Our model offers a powerful tool for analyzing sustainable competitive advantage in in the absence of traditional isolating mechanisms.

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FIGURE 1

Conceptual Model

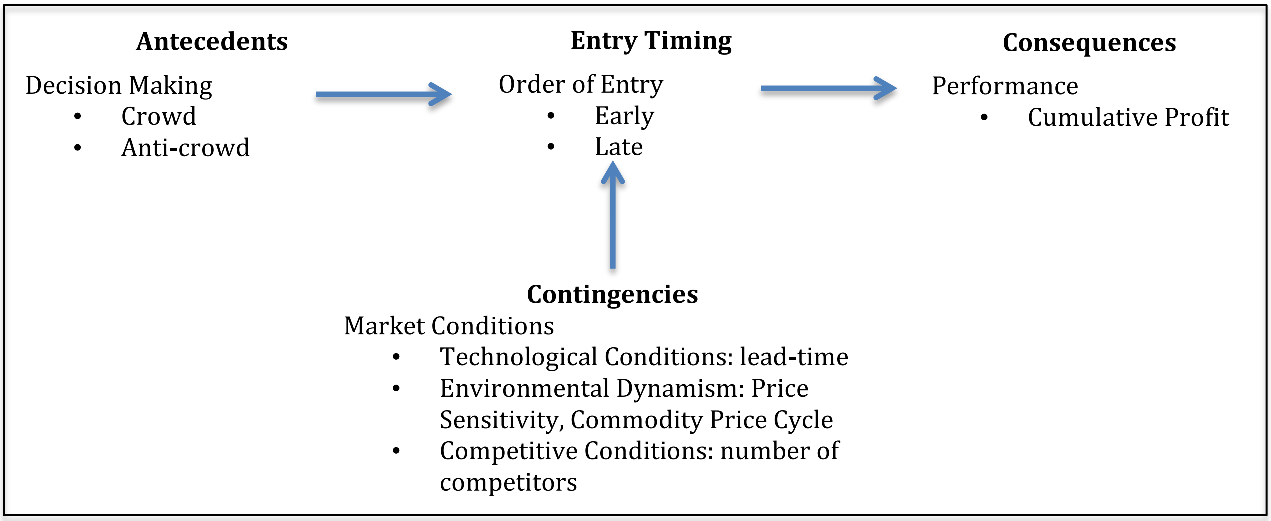

FIGURE 2

Model Decision Tree Red and White Grape Producers Minority Game

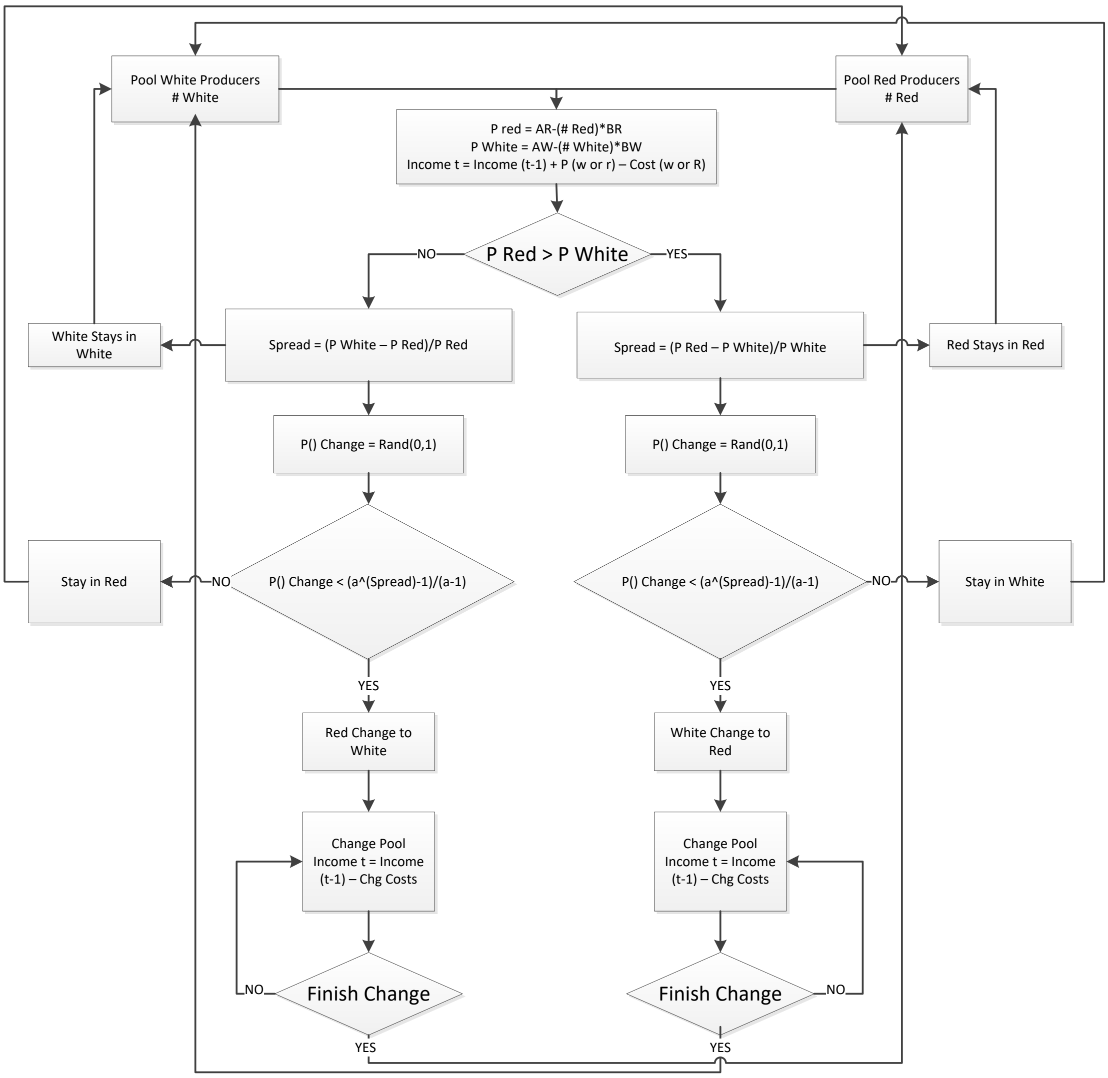

FIGURE 3

Price and Production Dynamics

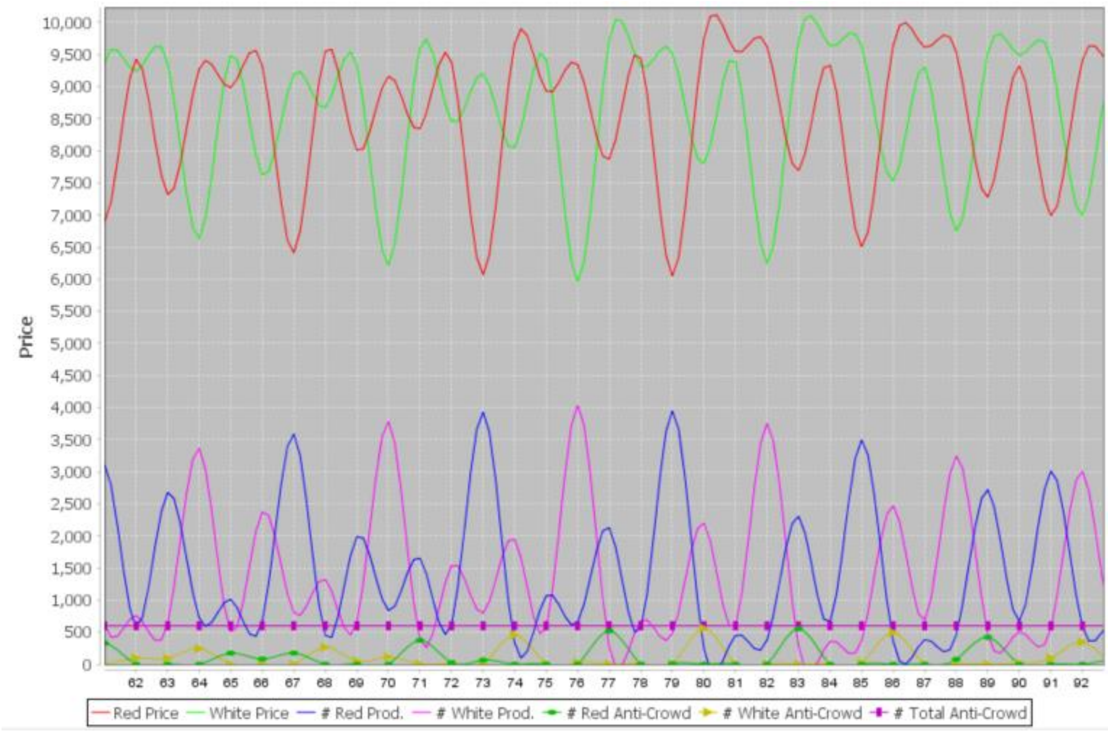

FIGURE 4

Cumulative Profit Comparison Crowd vs. Anti-Crowd Groups

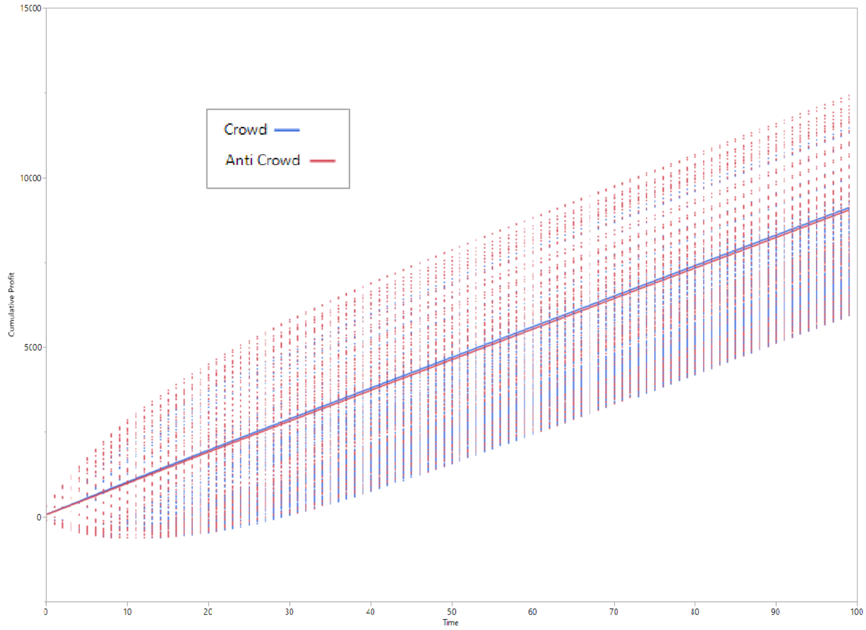

Figure 4a. Cumulative Profit Comparison Crowd vs. Anti-Crowd. Change Factor=100

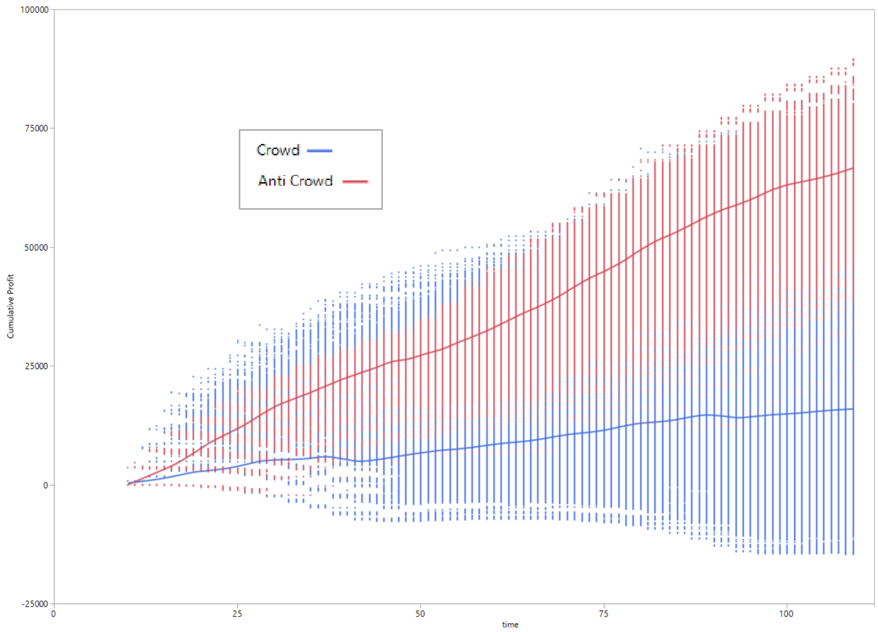

Figure 4b. Cumulative Profit Comparison Crowd vs. Anti-Crowd. Change Factor=0.001

Simulation parameters: Setup Time=2 years, Number of Crowd Competitors=7000, Number of Anti-crowd Competitors=700

FIGURE 5

The Crossed Impact of Price Sensitivity, Setup Time and Total Number of Competitors on Anti-crowd Performance

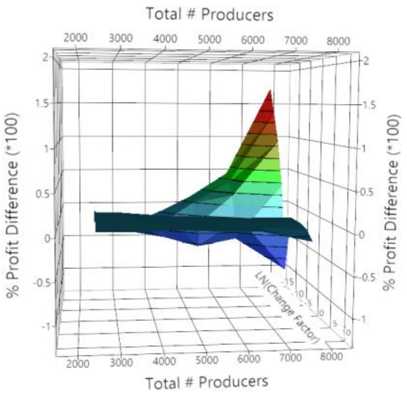

Figure 5a. Impact of Price Sensitivity (Change Factor) and Total # of Producers on Anticrowd Performance.

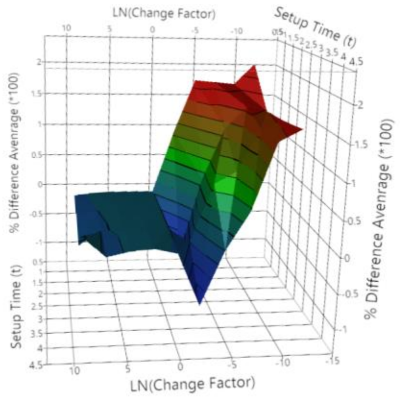

Figure 5b. Impact of Price Sensitivity (Change Factor) and Setup time on Anticrowd Performance.

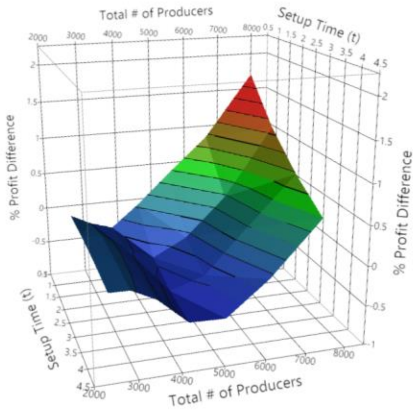

Figure 5c. Impact of Setup Time and Total # of Producers on Anticrowd Performance.

FIGURE 6

The Influence of % of Anti-crowd Competitors

on Anti-crowd Performance

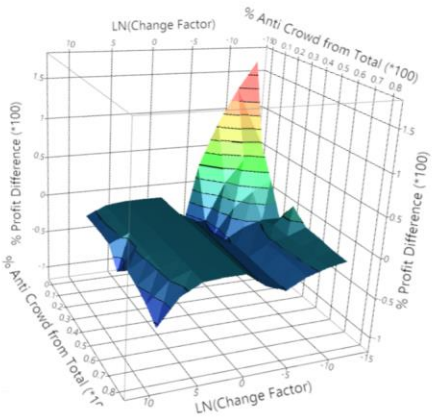

Figure 6a. Influence of % of Anticrowd Competitors and Price Sensitivity (Change Factor) on Anticrowd Performance

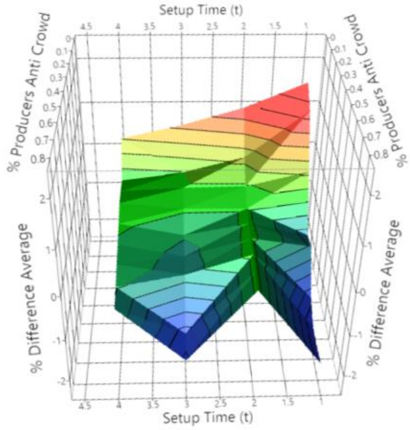

Figure 6b. Influence of % of Anticrowd Competitors and Setup Time on Anticrowd Performance

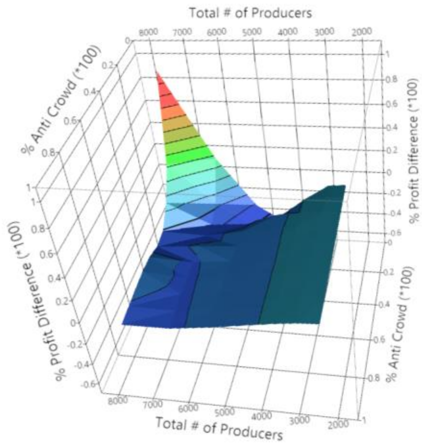

Figure 6c. Influence of % of Anticrowd Competitors and Total # of Producers on Anticrowd Performance

TABLE I

Model Initialization Parameters

PARAMETER	**INITIAL VALUES**
Number of Crowd Competitors – *CR*	7000
Number of Anti-crowd competitors – *AC*	700
% of White Producers	57%
Unit cost j – c_j	6000
Maintenance Cost (when switching production)	0
Demand Function Slope	-1
Crowd competitors sensitivity to change – λ (Change Factor)	0.001
Simulation span (Number of years) – *T*	100
Warm up period (Number of years) – *t*	10
Number of producers setting up during warm up period *k*	120
Setup Time - *s*	2
Number of replications (Monte Carlo runs)	70