

Saha, Atanu; Havenner, Arthur; Rauschenbach, Sonya

Article

The rise of dominant firms: The role of chance

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Research Article

Atanu Saha*, Arthur Havenner, Sonya Rauschenbach

The Rise of Dominant Firms: The Role of Chance

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Abstract: The principal explanations in the existing economics literature for the formation of concentrated markets are intellectual property-related entry barriers, economies of scale, and network effects. In each of these explanations, a few firms have an inherent advantage, allowing them to maintain their dominance. Our study's objective is to show that even when all firms are equally situated, an industry can evolve from a competitive to an oligopolistic structure purely as a result of random chance. We create a stylized model where firms are identical at inception, with none having any competitive advantage. In each period, a firm's profit is random with zero mean. The randomness of profits is hypothesized to stem from demand uncertainty and production cost fluctuations. Simulation results show that, solely as a result of chance, a competitive industry transitions to a market structure where only a handful dominate. The antitrust implications of our paper pertain to the causes of oligopoly formation. Notwithstanding that in some cases oligopolies can arise as a result of anticompetitive behavior of firms, we show that market concentration can also occur as a benign, natural consequence of evolution of an industry characterized by firms with uncertain profits.

Keywords: industry concentration, random chance, antitrust

1 Introduction

Competition is generally thought of as the fuel powering productivity and innovation. Understandably, antitrust bodies view with concern when market concentration increases in certain industries and dominant firms emerge. Classical economics provides many explanations for the presence or the rise of concentrated markets; the principal ones being intellectual property-related entry barriers, economies of scale, and government-mandated monopolies. Several studies, which we review later, have discussed these explanations of oligopoly formation. In each of these explanations, a few firms have an inherent advantage over their rivals, allowing them to form or maintain their dominance. However, when there is no idiosyncratic feature giving any firm an edge over its competitors, that is, when all firms are equally situated, classical theory does not provide an adequate explanation as to why many firms exit the market while a few emerge as dominant ones.

Classical economic theory posits that a competitive market with undifferentiated products should continue to be competitive indefinitely. Yet, in reality, we do observe competitive markets evolving into oligopolies, with few firms commanding significant market shares. Take, for example, the market for televisions, which has evolved from having myriad manufacturers in the 1980s to just a handful currently; Samsung alone commanded nearly 54% of the market in 2015. The market for eyewear saw a similar

*Corresponding author: Atanu Saha, Econ One, New York, UNITED STATES, E-mail: asaha@econone.com

Arthur Havenner, University of California, Davis, United States

Sonya Rauschenbach, Etsy, New York, United States

evolution; Luxottica currently manufactures around 80% of the eyewear sold.¹ Recently, an article in the popular journal *Economist* analyzed competition across a broad range of U.S. industries and found a general trend toward concentration.²

In this paper, we focus on an explanation of industry concentration that has received scant attention in the extant literature: the role of random chance. We demonstrate that chance plays an important role in the evolution of an industry from a competitive to a concentrated structure even when none of the firms enjoy the benefits of traditional factors such as economies of scale, brand recognition, consumer loyalty or network effects. We readily recognize that these factors, discussed extensively in the literature, do play an undeniably important role in the evolution of oligopolies. However, to isolate the role of random chance, we have deliberately created a simple, stylized model where, in each period, the firm's profits randomly change by a small, discrete, positive or negative amount (equal in absolute value), and firm's capital grows or shrinks depending on the changes in its profits. The firm exits the market if and when it fully exhausts its initial capital. The assumed amount of this discrete change is supported by empirical evidence, discussed later in the paper. We also assume that neither the firm's size nor its market share affects the likelihood or the amount of the daily profit change. Despite this stylized framework, we demonstrate through Monte Carlo simulations that the probability of the firm exiting the market increases steadily over time. In a multi-firm setting, we show there is a high likelihood that, over time, the industry would transition to a structure where only a few firms dominate with commanding market shares.

This result is somewhat unexpected and, at first glance, might not jive with intuition. Because we have assumed the small positive or negative change affecting the firm's capital is equally likely—just as in the toss of a fair coin—one might expect the firm's capital time-path to fluctuate around the mean. This expected outcome would be consistent with many prior studies that have contended that a firm's capital follows a mean-reverting process. Yet, we observe that the firm's capital time-path veers considerably away from the mean quite often, and the firm's losses become large enough to exhaust its entire starting capital much more frequently than one would expect. A key reason for this outcome is that the firm's capital time-path reflects the cumulative effect of small, discrete profit changes over time.

Another rather unexpected feature of our finding is that a long string of negative events (akin to many tails in a row) occurs more often than one would expect by random chance. An often-quoted passage of the Bible confers the devastating consequences of seven years of famine: "Seven years of great abundance are coming throughout the land of Egypt, but seven years of famine will follow them. Then all the abundance in Egypt will be forgotten, and the famine will ravage the land."³ Manifold interpretations notwithstanding, this passage highlights the asymmetric impact of a string of negative events. In this paper, we show that a string of ten or more negative events for the firm occur not infrequently, and such strings greatly hasten its demise. Another key factor that also contributes to the demise of the firm is the overall proportion of negative events experienced by the firm. This proportion is often observed to be considerably larger than the expected value of half.

The key finding of our paper is that an industry can evolve from a perfectly competitive setting to an oligopoly even when there are no traditional factors such as entry barriers, network effects or economies of scale, which are the generally accepted reasons for the rise of a few dominant firms. The practical implication of our findings is that they provide antitrust authorities an alternative explanation for the rise of dominant firms in an industry. While it is certainly true in some instances anti-competitive conduct could have been a key factor in the rise of dominant firms, our results show oligopolies can also arise as a benign, natural consequence of evolution of firms in an environment where the firm's profits fluctuate randomly from one period to the next, which is true virtually in all industries other than government monopolies.

In the next section, we review the relevant literature. In the third section, we motivate the importance of random chance by examining the time-path of winnings and losses in a simple coin-tossing game. In

¹ <https://www.reuters.com/article/us-samsung-elec-tv/how-samsung-fell-behind-sony-and-lg-in-the-premium-tv-market-idUSKBN1I24K2>; <https://www.forbes.com/sites/anaswanson/2014/09/10/meet-the-four-eyed-eight-tentacled-monopoly-that-is-making-your-glasses-so-expensive/#7879d506b66b>

² <https://www.economist.com/graphic-detail/2016/03/24/corporate-concentration>

³ Genesis 41.

the fourth section, we lay out the theoretical framework for the firm's profit and capital time-path and we then undertake Monte Carlo simulations. In this section, we also examine the key factors contributing to a firm's demise through a logit analysis. We then discuss the implications of our results in the fifth section and provide a few pieces of empirical evidence of increasing concentration in an industry characterized by undifferentiated products. The final section concludes with a discussion about the antitrust implications of our paper.

2 The Relevant Literature

Many studies have documented empirical evidence on the trend towards industry consolidation. These studies have examined a broad range of industries, from ones producing undifferentiated products to those where brand recognition is indispensable to product success. Many of these studies, as well as others, have focused on various factors contributing to market concentration. This literature review briefly describes how industry concentration has historically been explained, and then turns to the body of literature that has modeled a firm's random profits over time.

2.1 Documenting and Explaining Industry Concentration

Grullon et al. (2016) examine concentration in various industries and find a sharp decline in the number of publicly traded companies since 1997. They write that, "This decline has been so substantial that the current number of publicly traded firms in the economy is similar to the one in mid 1970s, when the real gross domestic product was one third of what it is today." Their study finds more significant evidence of concentration by looking at the Herfindahl-Hirschman index and average firm size, which it finds to be three times larger in 2014 than twenty years earlier. Also, their study observes that advantages from economies of scale, induced in large part by technology, were a driving factor behind the consolidation of industries. Gutierrez and Philippon (2017) confirm the general trend towards consolidation, however they do not find convincing evidence of technology playing a key role. MacDonald (2017), Gaynor and Haas-Wilson (1999) and Esteve-Perez (2012) all give industry-specific examples where technology-induced scale economies and resulting feedback effects led to concentrated markets. MacDonald (2017) is particularly important in the context of our paper, because it focuses on industries that generally produce undifferentiated products. They provide extensive evidence of industry concentration over time.

There is a rich body of literature describing the role of feedback loops and network effects in engendering market concentration. Economies of scale, which give larger firms' ability to reduce cost and increase efficiency, can create feedback loops where the larger firms get bigger by utilizing their scale-induced advantages over their competitors. Klepper (1996) introduces a theoretical model highlighting feedback loops between firm size, innovation, and market share. Numerous prior studies have discussed that network effect is a powerful driver of feedback loops and the rise of dominant firms. Network effects arise where the value of the product is enhanced as more consumers use it. Liebowitz and Margolis (1999) provide an excellent description of network effects in different industries.

2.2 Modeling a Firm's Stochastic Profits

There have been extensive discussions in the literature about which theoretical underpinning is most suited for modeling the random profits of a firm. Much of the debate has centered around whether firm profits follow a mean-reverting (i.e., stationary) or a non-stationary process. Among the early proponents of the mean-reversion hypothesis is Mueller (1986), who argues that if the market is competitive, a firm's profits will revert to its mean over time; in other words, the random profits of a competitive firm follow a stationary process. However, several studies have provided empirical evidence refuting the validity of

mean-reverting process for financial returns. For example, Canarella et al. (2013) examine panel data of different profitability metrics and find little evidence to confirm that the firm's profits revert to the mean. Other studies have used stochastic, non-stationary models in order to examine a firm's capital over time. For example, Tippet and Whittington (1995) examine various firms' accounting ratios and find that the only models consistent with the data are variants of random walk processes, that is, non-stationary models.

The study by Denrell (2004) is particularly relevant to this paper. He uses a random walk model to represent the firm's random cost of production. He shows that one firm's outperformance of its peers might not only be due to successful strategies but random chance as well. He highlights the importance of the 'cumulative character' of the random walk process and shows that it can lead to sustained bouts of outperformance of the firm. Another paper which highlights the importance of chance in firm profitability is Ma (2002). He addresses the importance of luck in the process of competitive advantage, and writes:

"Elusive as a theoretical concept yet certain in its earthly presence, luck, admit it or not, as a non-trivial determinant of performance, begs further understanding and should perhaps neither be conveniently reduced to the 'error term' in statistical analysis nor casually dismissed as being atheoretical. To date, there is rarely any formal effort that systematically explains how luck impacts on the gaining of competitive advantage and firm performance."⁴

His paper provides various examples of luck leading to market dominance. While his paper includes an excellent qualitative discussion of the role of chance, it does not contain an analytical framework to examine this phenomenon. Our paper builds on Sherer and Ross (1990), who provide an excellent analysis, modeling the role of luck in the process of industry concentration.⁵

In this paper, building on the prior literature, we propose a model where the firm's random profits are non-stationary. However, the key difference between our paper and the relevant prior studies is that those studies have attributed non-stationarity of profits and rise of dominant firms to technological innovation-induced competitive advantage. By contrast, in our paper, we assume all firms to be equally situated, with none enjoying any advantage over others. We demonstrate that many firms exit, and oligopolistic market structures rise over time, purely as a result of non-stationary, stochastic profits.

3 A Coin Tossing Game

To highlight the importance of chance in the formation of concentrated markets, we begin with a simple coin-tossing experiment.⁶ Suppose an individual begins a game with zero dollars and, based on the toss of a fair coin, wins (if heads) or loses (if tails) a dollar at each toss. So, for any toss, the expected value of the gain or loss is zero. If one were to create a line-graph of the cumulated gains and losses over time, one might expect that line to hover around zero, since the expected value of earnings for any toss is zero.

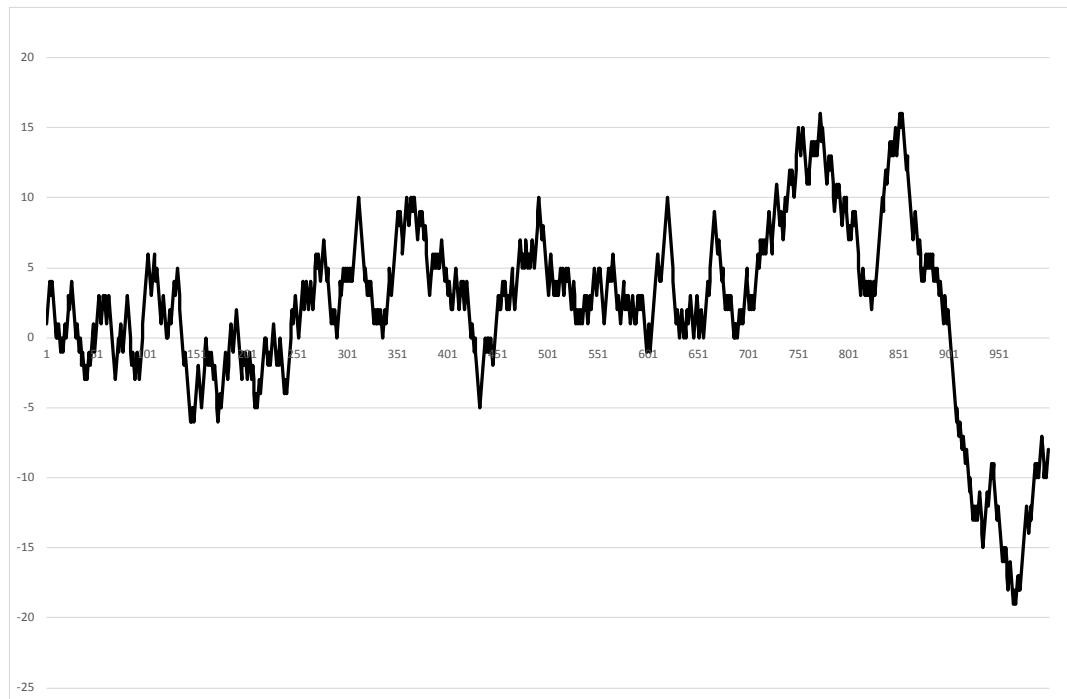
Below we show three examples of the pattern of the cumulative gains or losses over time, assuming the game continues for 1,000 tosses. In Chart 1A, the pattern is generally consistent with expectation, with the line representing the cumulated gain/loss crossing the horizontal axis at zero several times.

But, the next two Charts, 1B and 1C, show quite different patterns. In Chart 1B, the line dips below the horizontal axis only once after the first toss and never again over the next 999 tosses. The cumulative winnings grow fairly steadily over time, reaching a maximum of \$51. Chart 1C shows the opposite pattern: the losses increase progressively over time, reaching a minimum value of -\$78. These last two charts show that, while the expected value of the gains/losses is zero, the earnings over time can deviate considerably from the mean.

⁴ Ma, Hao. (2002). p. 525.

⁵ They conclude: "Why do concentrated firm size distributions arise...? The answer, in a word, is luck." Sherer and Ross (1990), p.142.

⁶ Various aspects of this experiment have been discussed in prior studies, including Feller (1950) and more recently Mandelbrot and Hudson (2012).

**Chart 1 A:** Cumulative Gain-Losses Over Time of the Coin Tossing Game**Chart 1 B:** Cumulative Gain-Losses Over Time of the Coin Tossing Game

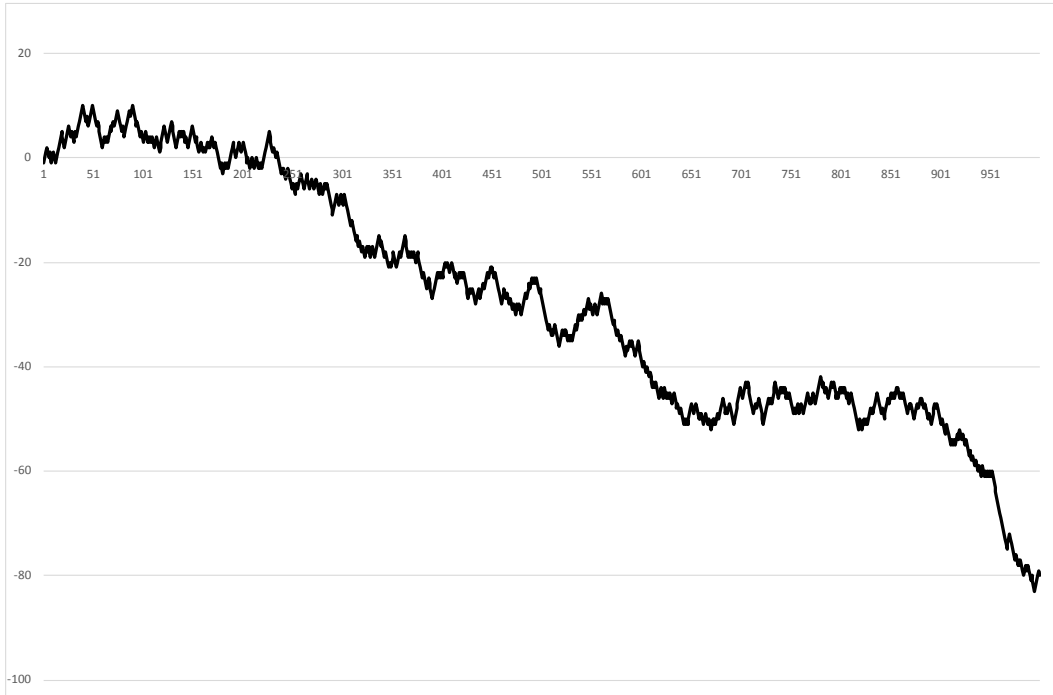


Chart 1 C: Cumulative Gain-Losses Over Time of the Coin Tossing Game

To analytically examine the observed phenomenon, define the earnings from a single toss by the random variable: $\tilde{r}_t = \pm 1$, and the *cumulated* earnings after T tosses as $c\tilde{r}_T = \sum_{t=1}^T \tilde{r}_t$. Then the mean and the standard deviation of the cumulated earnings after T tosses are:

$$\mu^c = E[c\tilde{r}_T] = 0 \text{ and } \sigma^c = \sqrt{E[c\tilde{r}_T^2] - E[c\tilde{r}_T]^2} = \sqrt{E[c\tilde{r}_T^2]} = \sqrt{\sum_{t=1}^T E(\tilde{r}_t^2)} = \sqrt{T}.$$

Thus, the variance of the cumulated earnings grows with the number of tosses, denoted by T . Expressed differently, the likelihood that the time-path of the earnings will veer away (in either direction) from its long-run average value grows as the length of the path increases. This result will have important implications for the likelihood of the demise of firms, discussed next.

4 The Theoretical Framework

In this section, we present a stylized model of a firm's capital time path. As in the coin-tossing example, we assume that the firm's profit moves up and down by a discrete amount in each period. This profit fluctuation can occur for a variety of reasons, including changing consumer demand, and/or fluctuating production costs. However, there are two significant differences between the coin-tossing example and the firm model: first, the firm begins with some start-up capital, and not zero; second, while in the coin-tossing example, the losses could grow indefinitely, here we assume that the firm exits when its initial capital is fully exhausted.

We assume that the firm starts with an initial capital of R_0 . At each period, t , the price-taking firm's random profit is given by:

$$\tilde{\pi}_t = Q_t \cdot (\tilde{p}_t - \tilde{c}_t) \quad (1)$$

where the firm's output is denoted by Q ; the firm faces random price, \tilde{p} , and its random marginal cost is \tilde{c} . The randomness in price can stem from a variety of factors, including changing consumer demand and random market shocks. Similarly, the randomness of marginal costs could be a result of uncertain input costs, among other factors. At any period, the firm's capital, which has an initial value of R_0 , can be written as:

$$\tilde{R}_t = \tilde{R}_{t-1} + \tilde{\pi}_t, \quad t = 1, \dots, T \quad (2)$$

With minimal loss of generality, and consistent with Sherer and Ross (1990), assume that at any period, the firm's random profit has two possible outcomes: positive or negative. Specifically, assume that in each period the random variable $\tilde{\pi}_t$ takes only two values (-1 or $+1$) with equal probability.⁷ In other words, the probability of the firm experiencing positive ($\pi_t = +1$) or negative ($\pi_t = -1$) profit is identical in each period and is equal to $1/2$.

Thus, the firm's stochastic capital follows a random walk process. This feature of our model is consistent with prior studies, including Trippett and Whittington (1995) and Denrell (2004). Following Harvey (1993, p.113), one can use repeated substitution of prior values to derive the expression for the firm's capital at any point in time $\tau \leq T$ as:

$$R_\tau = R_0 + \sum_{t=0}^{\tau} \pi_t \quad (3)$$

Since the random variable $\tilde{\pi}_t$ has zero mean and unit variance at all periods, one can utilize (3) to derive the expression for the mean and standard deviation of the firm's capital at any period $\tau \leq T$ as:

$$\mu_\tau = R_0 \quad \text{and} \quad \sigma_\tau = \sqrt{\tau} \quad (4)$$

As in the coin-tossing game, while the firm's mean capital is independent of time, the variance of the firm's capital grows with the length of the time-path. It is assumed that the firm ceases to exist at any period τ if it exhausts its capital, that is if $R_\tau = 0$.

The figures (Chart 1 A-C) for the coin-tossing game provide a visual representation of the possible patterns of the firm's capital over time, with two differences: the horizontal axis is R_0 and not zero; also, if and when the firm's capital hits zero the time-path ceases.

Derivation of an analytical solution for the firm's cessation probability (i.e., $\Pr[R_\tau = 0]$) is extremely difficult.⁸ However, one can obtain a sufficiently precise estimate of this probability through numerical methods of a Monte Carlo simulation.

4.1 Simulation Details

In the Monte Carlo simulation, the time-path of the firm's capital is computed over various lengths of time ranging between zero and 5,000 periods i.e., $T \in [0, 5000]$. It is assumed the firm's initial capital, R_0 , is 50.

At each period, a uniformly distributed random variable (constrained to be between zero and one) was generated; the firm was then assumed to experience positive (negative) profit if the realized value of the uniform random variable as greater (less) than or equal to 0.5. We then used equation (2) above to compute the time-path of the firm's capital. This process was repeated 50,000 times, the number of iterations in the Monte Carlo simulation. For each iteration, we recorded whether the firm's capital at any point in the time-path was equal to zero; if it was, we recorded it as a firm-cessation event and the firm's capital time-path ceased to exist beyond that point. The average number of cessation events across the 50,000 iterations yielded the empirical estimate of the firm's cessation probability.

⁷ This is akin to some simple evolutionary models where a binary outcome in each period leads to complex outcomes over time. See, for example, Nikolettseas et al. (2008), which looks at outcomes of hawk and dove interactions to gauge dominant species competition, or Kondor et al. (2018) which applies a binary particle spin outcome of a physical model to sociological systems.

⁸ If one assumes that the firm's random profit is normally distributed, then one can use the closed-form solution for the probability of the firm's capital hitting a barrier-value of zero. See Elliott and Kopp (2005), Chapter 7.

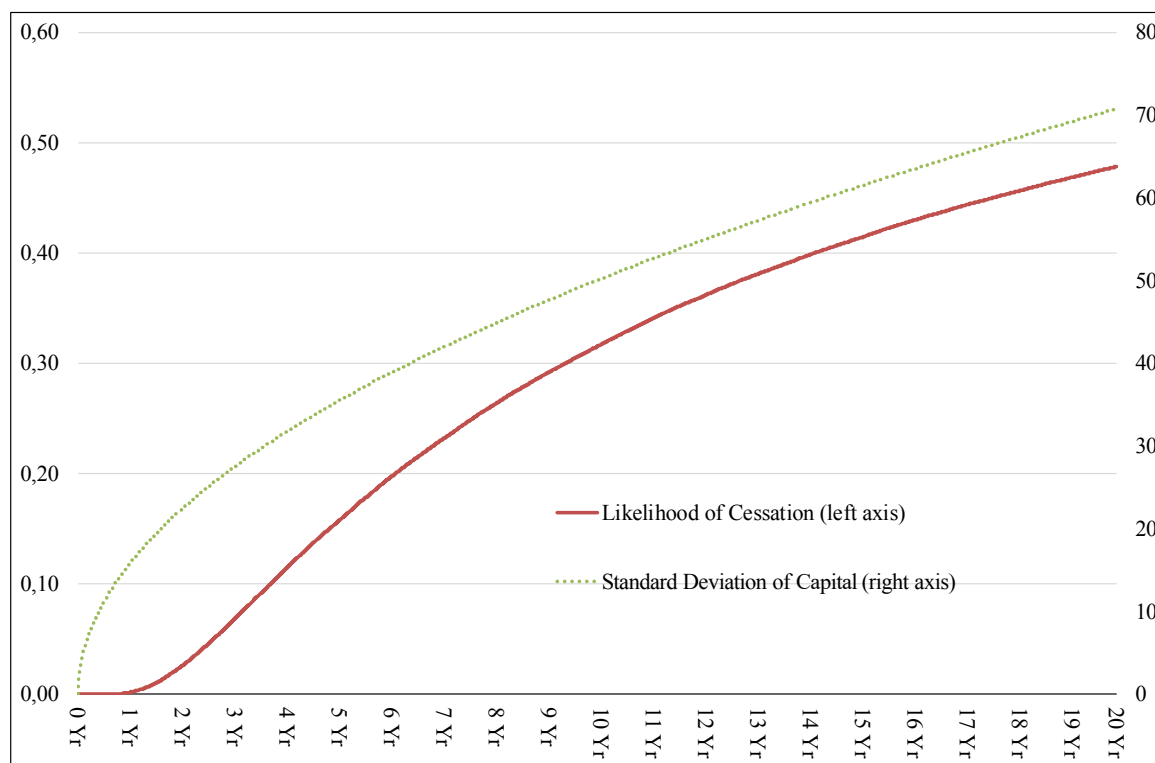


Chart 2: Cessation Probability Over Time

In Chart 2, we depict the empirical estimates of the firm's cessation probabilities as the length of the time-path increases from zero to 5,000 periods. For the ease of exposition, henceforth in this paper, we will characterize a period to be a business day; thus, a time-path of 1,000 periods corresponds to approximately 4 years and 5,000 periods corresponds to about 20 years. As can be seen from Chart 2, the firm's cessation probability increases, purely as a result of chance alone, by approximately by 0.1 for every 4-year increment in the length of the time-path.

In Chart 2, we also depict the value of the standard deviation of the firm's capital over the various lengths of the time-path. Chart 2 shows that the firm's cessation likelihood has a close correspondence with the standard deviation of its capital. Given the findings of the coin toss example discussed earlier and the fact that the variance of the firm's capital grows with time, this result seems eminently plausible.

4.2 The Effect of a String of Negative Profit Days

An important area of examination is the factors that contribute to the demise of a firm. We hypothesize that an important factor is a string of negative profits days experienced by the firm. We thus created a variable called 'string-length' which is the maximum number of consecutive negative profit days the firm experienced within its time-path. The value of 'string-length' was recorded for each iteration of the Monte Carlo simulation.

Chart 3 shows the histogram of the variable 'string-length', depicted by the bars in the chart; the height of the bar corresponds to the frequency of occurrence of the particular value of string-length. In this chart, the line graph shows the conditional probability of firm's cessation, i.e., the observed probability of the firm's demise, *given* it experienced a string-length of certain size. Both these variables in the chart were computed using a time-path of 4 years.

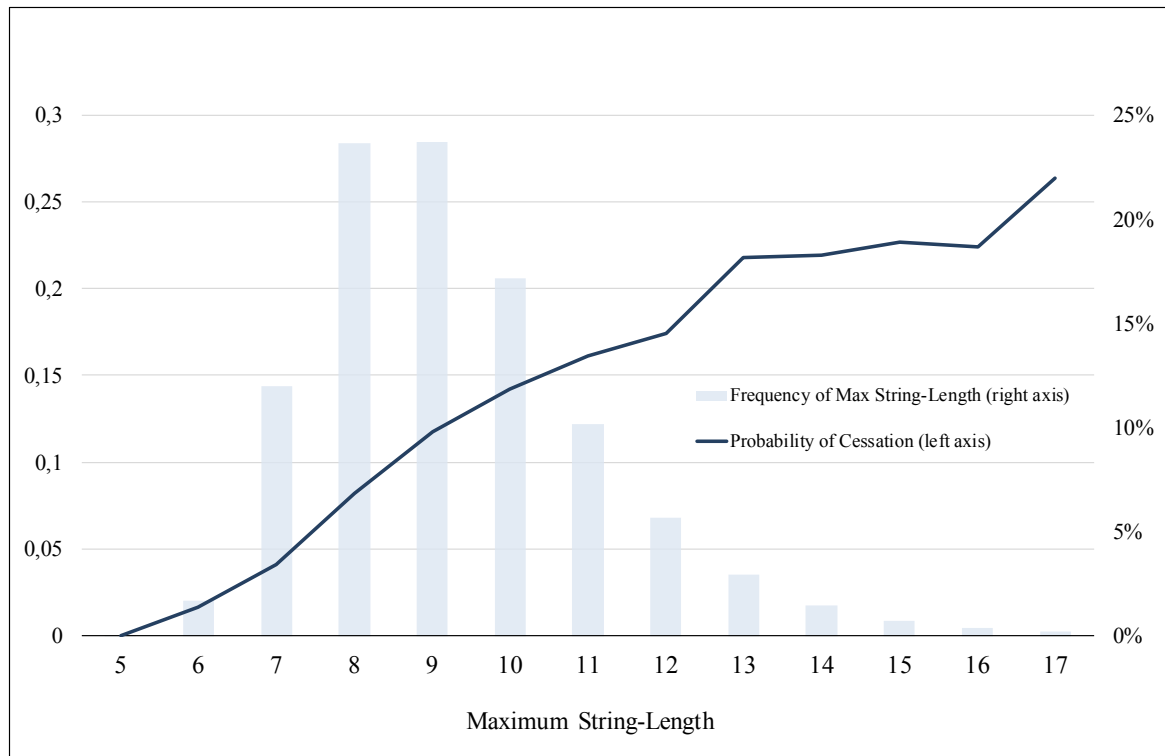


Chart 3: Maximum String-Length and Cessation Probability

The histogram shows that the most frequently occurring string-length is 9 (occurring 23.7% of the time), closely followed by 8 (occurring 23.6% of the time). In fact, a string-length of 10 or more occurs nearly 39% of the time!

Not unexpectedly, the likelihood of observing a given string diminishes rapidly with the length of the string. However, the probability of a firm's exit rises steadily as it experiences longer strings of negative profit days. For example, the average (unconditional) probability of a firm's exit within 4 years is 0.116. But, if the firm experienced a string-length of 15, then the firm's cessation probability nearly doubles to 0.22.

4.3 The Effect of Cumulated Capital

A factor likely to have an opposite effect from the string of negative events is the size of the firm's cumulated capital. If the firm's cumulated capital, for example, had reached 100 (i.e., double the starting value of 50), then it is far more likely to withstand a long string of negative events than if a firm's cumulated capital had dropped to 20. To examine this factor, we created a variable 'maximum-capital-ratio', which is the maximum value of the firm's capital over the 4-year time-path divided by the starting value of 50. At each iteration of the Monte Carlo simulation, we recorded the value of this variable. We should expect to see that this maximum-capital-ratio variable to have a dampening effect on the firm's likelihood of exit.

Indeed, as Chart 4 shows, the likelihood of a firm's exit is negatively related to the maximum-capital-ratio. For those firms with a maximum-capital-ratio around 1, signifying that the firm's capital never surpassed the starting value, the likelihood of exit is around 50%. There is a steep drop-off of the exit probability once a firm reaches the maximum-capital-ratio of 1.2, which is only 20% higher than the starting value.

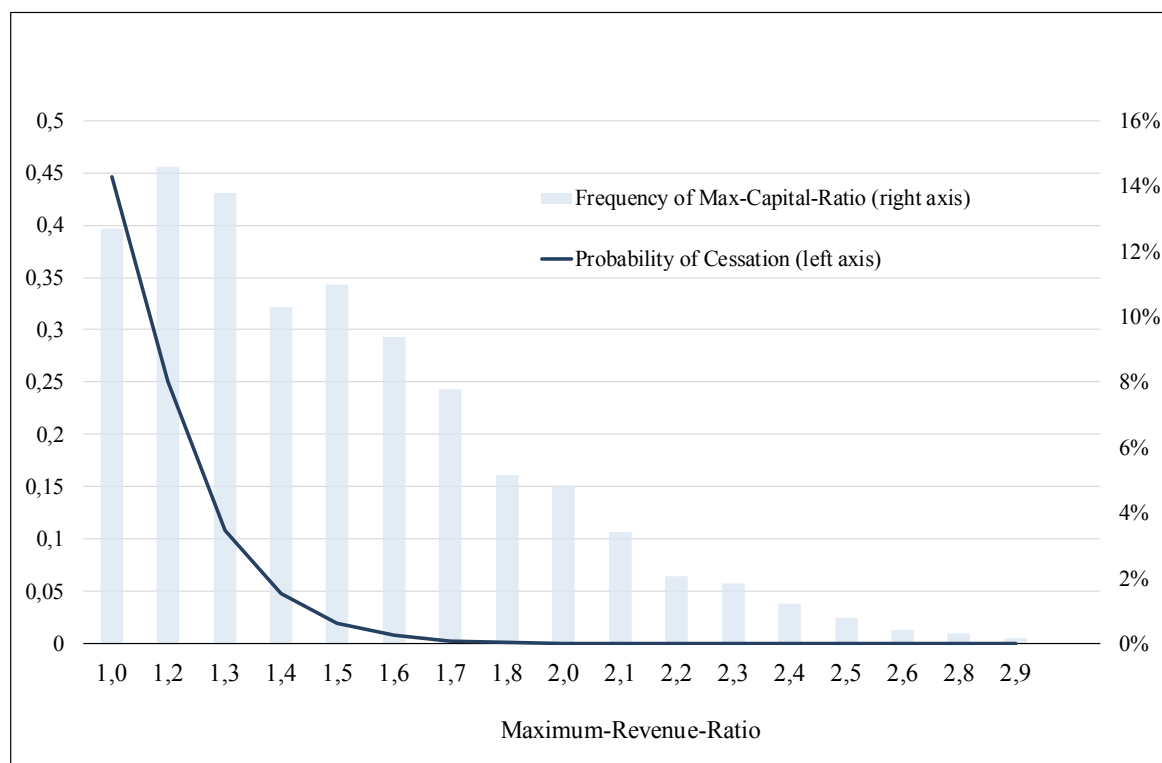


Chart 4: Maximum-Capital-Ratio and Cessation Probability

4.4 The Effect of Overall Negative Profit Days

Finally, the most obvious factor likely to affect the firm's cessation probability is the overall proportion of negative profit days experienced by the firm. In each iteration of the simulation, we recorded the proportion of negative days within the firm's time-path. We found that across the 50,000 iterations, the mean and median proportion of negative days is indistinguishable from $\frac{1}{2}$, which is to be expected given the construction of the random variable affecting the firm's profit. However, because of the inherent randomness of this variable, each iteration of the simulation will not yield exactly an equal proportion of negative and positive days within the time-paths. We would expect the variable 'proportion of negative days' to increase the likelihood of a firm's demise.

4.5 Summary Statistics on Key Variables and Logit Regression Results

Table 1 below contains the summary statistics of the three key variables affecting the firm's cessation probability: (a) string-length; (b) maximum-capital-ratio, and (c) proportion of negative days. In addition, we also report the summary statistics on two additional variables: the binary variable, indicating whether the firm has ceased to exist; and the firm's average capital over its time-path. These variables were computed from data generated through the Monte Carlo simulation, using 50,000 iterations.

As noted earlier, the mean and median proportion of negative days are indistinguishable from 0.5. Relatedly, the average value of the firm's capital is not statistically different from 50, which is the firm's initial capital. That said, the firm's average capital has a wide dispersion around its mean, as reflected in its minimum and maximum values; this is consistent with the large dispersion of the variable maximum capital ratio. Indeed, these two variables, maximum capital ratio and average capital are highly correlated

to each other. As a result, we chose to use only the maximum capital ratio variable as the regressor in the logit regression.

Table 1: Summary Statistics on Monte Carlo Simulation

Variable	Min	Median	Mean	Max	Standard Deviation
Cessation (Binary)	0,000	0,000	0,116	1,000	0,320
String-Length	5,0	9,0	9,3	25,0	1,9
Maximum-Capital-Ratio	0,980	1,420	1,493	3,840	0,381
Proportion of Negative Days	0,438	0,500	0,500	0,568	0,016
Average Capital	2,722	50,048	50,075	121,246	18,188

Note: Cessation is a binary variable with a 1 indicating cessation. Average Capital is the average over the entire time period. The Monte Carlo simulation was conducted with 50,000 iterations.

The logit model's explained variable is a binary variable which took the value of one if the firm ceased to exist within 4 years, and zero otherwise. Table 2 contains the results of the logit analysis. These results show that all three variables have a statistically significant effect on the probability of the firm's demise; the estimated coefficients of the variables have the expected sign and are highly significant. There is fair a degree of collinearity among the regressors, which reduces the z-statistics of the estimated coefficients though they remain highly statistically significant.⁹

Table 2: Logit Regression Results

Explained Variable: Firm Cessation (Z-Stats are in Parenthesis)	
	Estimate:
String-Length	0.69 (5.66)
Maximum-Capital-Ratio	-4.36 (-24.11)
Proportion of Negative Days	291.48 (67.82)
Pseudo R2	0,667

The results of the logit analysis indicate that the following three factors have statistically significant effects on the probability of a firm's demise: a string of negative profit days, the overall proportion of negative profit days, and the extent to which the firm's cumulative capital has deviated from the initial value. If the firm's cumulative capital is large and many fold larger than the initial value (that is, if the firm has grown considerably in size) then it can withstand negative profit shocks; thus, a larger cumulative capital has a negative impact on a firm's demise probability.

Up to this point, we have examined the capital path of a single firm. We now consider an industry that has multiple firms, each with identical capital dynamics laid out in equations (1)-(3). We also assume that each have identical starting capital. Expansion of our analysis from a single to multiple firms will allow us to examine how the demise of firms leads to the concentration of the industry over time.

For ease of exposition, we assume that there are five firms; our results are qualitatively the same regardless of the number of firms. In this Monte Carlo simulation, we not only tracked the capital over time of each of the five firms, but also the time-path of their market shares (i.e., a firm's capital as a percent of the sum of capital of all firms). Below we depict two examples of the patterns of the time-paths of the market shares of the firms over a 4-year period. In the first example, a monopoly is formed, as four out of the five firms exit the market. While in the second example, two firms survive, giving rise to a duopoly.

⁹ If the regressors are included individually, then the z-statistics of the three regressors, string-length, maximum capital ratio and proportion of negative events, are 30.43, -67.34, and 67.82, respectively.

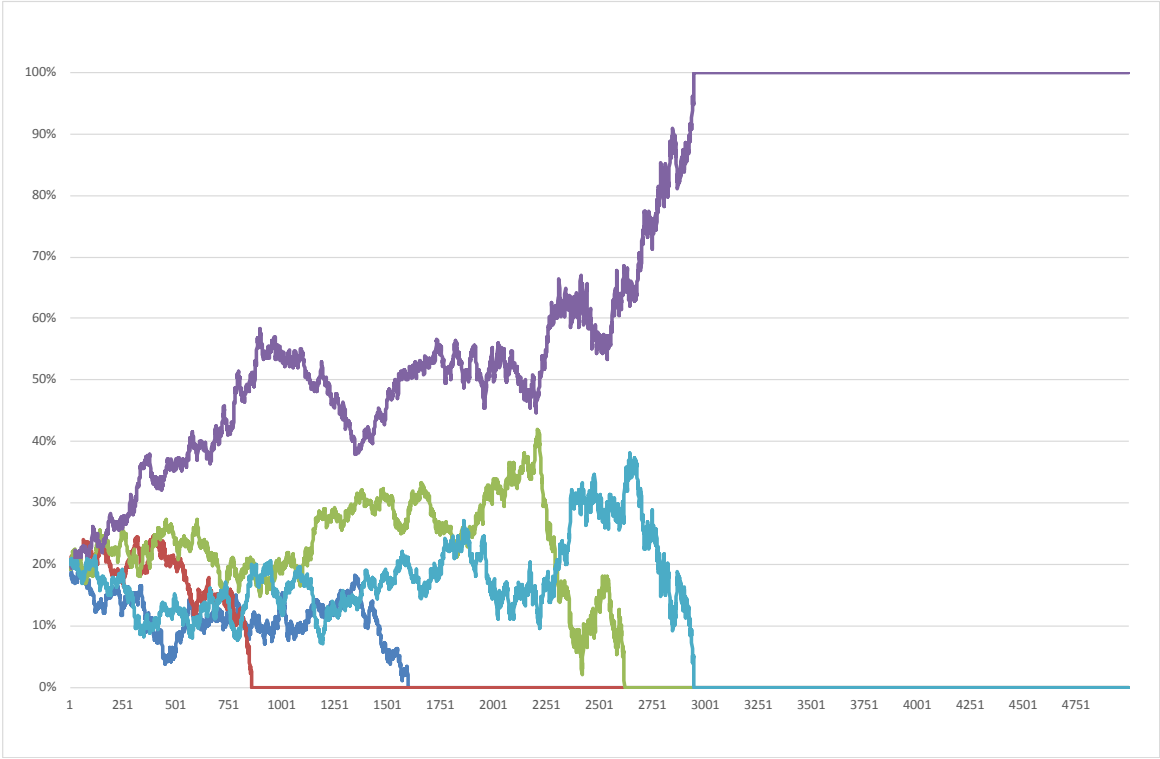


Chart 5a: Market Shares Over Time (Five Firms)

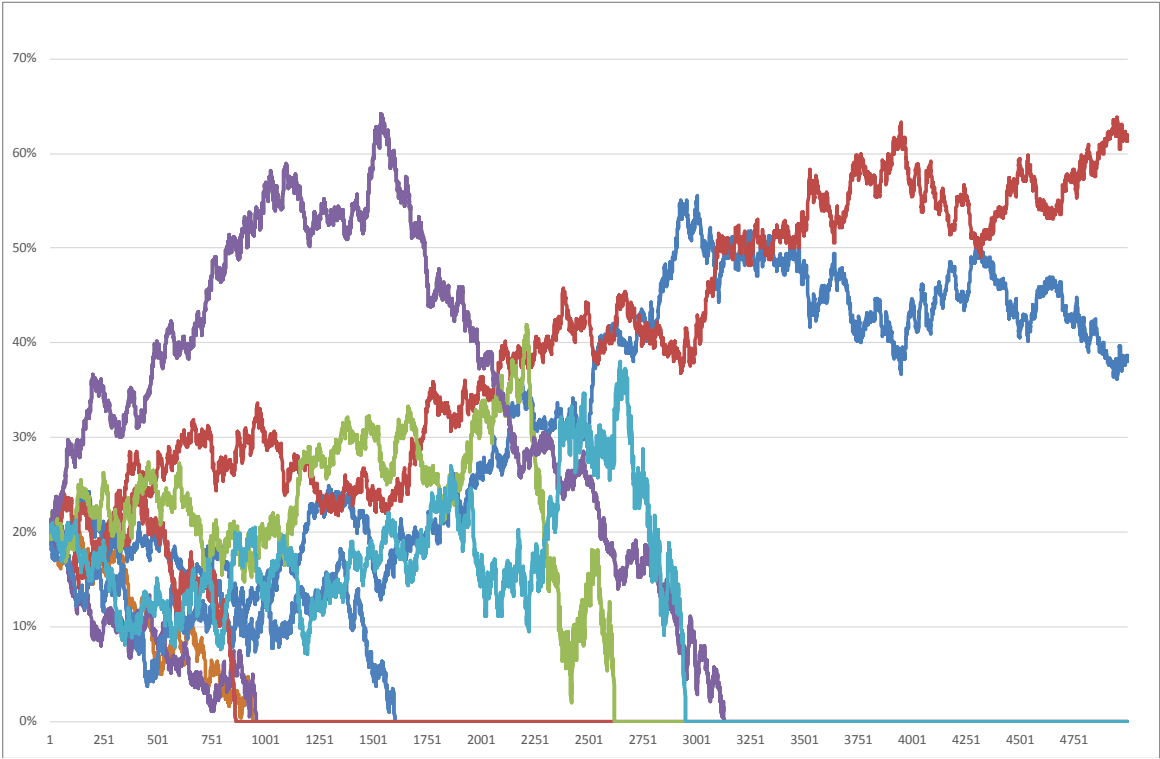


Chart 5b: Market Shares Over Time (Five Firms)

Table 3 below shows the various outcomes of firm exits over the 4-year and 20-year time horizons. As before, these outcomes were generated using a Monte Carlo simulation using 50,000 iterations.

Table 3: Market Outcomes Based on Five Firms at Inception

	Path-length:	
	4 Years	20 Years
All Firms Compete	55%	4%
Only 1 Firm Exits	35%	18%
Only 2 Firms Exit	9%	32%
Duopoly	1%	30%
Monopoly	0%	14%
All Firms Exit	0%	3%

Table 3 shows that when the length of the time-path increases, it becomes increasingly likely that a firm will exit. In the 4-year scenario, there is a 45% chance that at least one firm will exit; by contrast, in 20 years, this chance rises to 96%. Importantly, the likelihood of a monopoly or a duopoly formation rises from 1% in 4 years to almost 44% in 20 years. These results are generally consistent with Sherer and Ross (1990).

Incidentally, we have undertaken a similar simulation exercise with 50 firms at inception instead of 5; we find the results to be qualitatively the same, except that the time horizon over which duopoly or monopolies form is longer. These findings demonstrate the unmistakable imprint of chance on market concentration: over time as the industry matures, it becomes increasingly concentrated. Yet, in our stylized model, the *only* driving factor behind any firm's demise is the small, discrete, random changes in its profits each day.

5 Discussion of the Results

As noted above, a crucial assumption of the paper's model is the daily discrete change in a firm's capital. The likelihood of firm's cessation is highly dependent on the assumed amount of this change. In the simulation model, the amount of daily change is $\frac{\pm 1}{50} = \pm 2\%$ (relative to the firm's long-run average capital). An important question is whether this assumption is realistic. This question is addressed below in several ways.

First, the assumption of a 2% daily change in either direction with equal probability translates to an annualized volatility of 31.6%. To view this in context, consider the fact that the Dow Jones Industrial Average, an index of some of the largest global companies, has an annualized volatility of 17.5%. However, the volatility for the constituent individual stocks' returns is much higher. The average annualized volatility of stocks for the individual Dow constituent companies is 30.1%.

Stock prices, however, are influenced by many factors, most importantly by the firm's net revenues or earnings. We gathered data on the quarterly earnings of the 30 firms that constitute the Dow Index. Using quarterly data on earnings since 1990, we computed the percent annual earnings change (i.e., year-over-year change in each quarter) for each of the Dow firms. Earnings are notoriously volatile because of one-time charge or income. Therefore, we removed the outliers in the data on earnings change by capping the percent change at the 90th percentile for the positive changes and at the 10th percentile for the negative changes.

Table 4 below shows the average values of the annualized volatility of Dow 30 firms' daily stock price returns and of quarterly earnings changes from 1990 through 2017. Indeed, the average standard deviation of quarterly earnings change is generally consistent with that of these firms' stock returns.

Table 4: Statistics for Individual Dow 30 Constituents

	Average Annualized Standard Deviation
Daily Stock Price Return	30,07%
Yearly Change in Quarterly Earnings	37,07%

In light of these figures, our assumption of a 2% daily change (or 31.6% annualized) in the firm's capital seems reasonable, particularly because we are modeling the capital time-path of relatively small firms producing homogenous goods and not of large, well established firms with brand recognition, as in the Dow Index.

As noted earlier, in our model we have not assumed any of the traditional factors that have been attributed to market concentration such as brand differentiation-induced consumer loyalty, network effects, or economies of scale. Had we assumed any of these factors, then the demise of many firms and the ensuing concentration of the industry could have been easily explained. By contrast we have modeled each firm to be identical, each producing perfectly homogenous products and each facing the same random process of drawing a positive or a negative event daily. This random profit environment is likely to be true for virtually all firms in any industry characterized by unpredictable changes in consumers' demand or fluctuations in input costs and hence the firm's profits.

We have specifically modeled the firms without any of the traditional features that provide a competitive edge to isolate the importance of chance as a key factor contributing to industry concentration. In this context, it is important to note that the random process in our model precludes the possibility of 'jump risks'. Many studies in the finance literature have modeled jump risks, where a sudden event, often unexpected, causes a large movement in stock prices.¹⁰ In the context of the firm, a jump risk would mean the possibility of a large random movement up or down in its capital. A large downward jump in capital could certainly explain the demise of firms. Yet, we demonstrate that, even in the complete absence of jump risks, a simple process of small, discrete changes in the firm's capital, caused by chance and chance alone, can explain the demise of many and the rise of a dominant few firms.

5.1 Empirical Evidence

An empirical analysis of the changes in concentration in various markets is beyond the scope of this paper. Here we provide a few pieces of evidence from the agricultural sector because most industries within this sector are characterized by two key features integral to our model: (a) they are dependent on the vagaries of weather and unpredictable output and input prices; as a result, they routinely experience the effect of random chance; and (b) agricultural industries typically produce undifferentiated products.

In the early 1900s, most agricultural production was from numerous family farms. Over time this industry has experienced a considerable degree of consolidation. Table 5 shows the percent change in four-firm concentration ratios for U.S. agribusinesses in the 25-year period between 1977 and 2012. In milk production and steer and heifer slaughter, the four-firm concentration ratio has more than doubled over this period. Many other industries have also experienced marked increases in concentration between 1997 and 2012.

The evidence in Table 5 highlights that even industries producing homogenous goods do become concentrated over time. While agricultural industries have undergone consolidation in large part due to technological change-induced scale economies, our results indicate that simple chance is also likely to have been an important contributing factor.

¹⁰ See for example Mandelbrot (1963), Akgiray and Booth (1988), or Hols and de Vries (1991).

Table 5: Four-Firm Concentration Ratios (CR4) in Selected U.S. Agribusiness

	Beginning year (1977) Year=1977	Ending year (2012) Year=2012	Change	% Change
Fluid milk processing	18	46	28	156%
Flour milling	33	50	17	52%
Wet corn milling	63	86	23	37%
Soybean processing	54	79	25	46%
Rice milling	51	47	-4	-8%
Cane sugar refining	63	95	32	51%
Beet sugar	67	78	11	16%
Steer and heifer slaughter	36	85	49	136%
Hog slaughter	34	64	30	88%

Note: Steer and Hog slaughter data start in 1980.

Sources: MacDonald (2017); U.S. Census Bureau; USDA Agricultural Marketing Service; Farm Journal; USDA Grain Inspection, Packers and Stockyards Administration.

6 Concluding Comments

In this paper, we have shown that chance plays an important role in the evolution of an industry from a competitive to a concentrated market structure even when none of the firms enjoy the benefits of entry barriers, economies of scale, brand recognition or network effects. To underscore the role of random chance, we have deliberately created a simple, stylized model where firms are identical at inception, with none having a competitive advantage. In each period, a firm's profits randomly fluctuate by a small, discrete, positive or negative amount, and the firm exits the market when it fully exhausts its initial capital. Despite this stylized framework, we have shown through Monte Carlo simulations that the probability of the firm's exit increases steadily over time, and in a multi-firm setting, a competitive industry transitions to a market structure where only a handful dominate.

The antitrust implications of our paper pertain not to the effects of but rather to the causes of oligopoly formation. Notwithstanding that in some cases oligopolies arose as a result of nefarious activity of a few firms, we have shown that market concentration can also occur as a benign, natural consequence of evolution of firms in a random environment. Unlike classical economic theory that proclaims competitive firms would continue to stay competitive indefinitely, our results show just the opposite: a competitive environment will naturally evolve over time—without violating any antitrust statutes—into a setting where a few firms dominate.

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