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The Effect of the Chartist to Fundamentalist ratio on Stock Market Price Formation. An ABM approach.

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"Speculative bubbles do not end like a short story, novel, or play. There is no final denouement that brings all the strands of a narrative into an impressive final conclusion. In the real world, we never know when the story is over."

Robert J. Shiller

Riksuniversiteit Groningen

Abstract

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This paper elaborates on the effects of agent heterogeneity on stock price formation in an over the counter market employing an agent based modeling approach. Two types of investors are considered: fundamentalists and chartists. Fundamentalists attempt to calculate the intrinsic value of a stock given their recollection of the profits and dividends a firm makes and issues. Chartists base their investment strategies on price trends. While fundamentalists tend to bring prices close to the firms fundamental value, chartists cause prices to follow previous trends. This study puts special emphasis on the ratio of one type of agent to the other.

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1 Introduction

Traditionally, asset pricing theory has argued that rational arbitrage forcibly approximates stock prices closer to their fundamental value (Friedman, 1953). This theory has been widely criticized for not including investor behavior which in recent times has accumulated enough statistical evidence that makes obvious its effect on market prices (Brown & Cliff, 2005) (Brown & Cliff, 2006) (Verma & Soydemir, 2009) (Baker, Wurgler, & Yuan, 2012). Chiang and Zheng (2010) find evidence of chartist behavior in advanced stock markets (with the exception of the US) and in Asian markets. They also conclude that crises trigger chartist activity in the country where the crisis is originated and propagates to other markets. During periods of crisis, they find supportive evidence for chartist behavior in the US market. A recent case exemplifies the propagation of chartist behavior in a crisis was the valuation of houses in the end of the housing boom of 2007 where Piazzesi and Schneider (2009) showed evidence that the number of people who believed it was a good time to buy a house grew as the boom came to an end. Yet, crises are not only caused due to the predominance of chartist behavior. (Blanchard & Watson, 1982) conclude that bubbles, in many markets, can occur given rationality. Phenomena such as runaway asset prices and market crashes work in accordance with rational bubbles. In addition to these studies, Huang, Zheng, and Chia (2010) find that the interaction between fundamentalist and chartist agents can also lead to financial crises.

The main goal of this paper is to contribute to the existing literature on the effect the chartist-fundamentalist (C-F) ratio has on stock market price formation. To do so, an agent based model (ABM) is used to build two tipes of agents: fundamentalists and chartists. This has proven to be a fruitful way to study financial markets, as it allows a better observation on how the interactions of heterogeneous agents can result in periods of stability and high price volatility in markets through emergent behavior. When referring to complex systems, the concept of equilibrium causes debate as it is often considered to be optimistic and a simplified view of reality that composes a minority of scenarios as opposed to being a norm. For this reason, this concept is used to identify a period of relative tranquility in a complex system, without implying that equilibrium is a natural tendency of real financial stock markets. As will be revised in section 2. there has already been a number of studies conducted using ABM which study the effect of the C-F ratio given different assumptions. In most cases, the market mechanism makes use of a market maker in order to determine market stock price. Another practice that distinguishes this paper is that in other work, fundamentalist agents do not derive the value of a stock from the profits of a firm, and instead it is assigned to them. This thesis has evaluated these approaches and attempts to contribute to the academic literature by presenting conclusions based on a ABM that is founded on different concepts that have allowed describing real market places while maintaining a relatively simple model. In first place, there is no market maker as an over the counter (OTC) market mechanism is employed. This implies that there is no central dealer that quotes buy and sell prices, but instead traders meet (today, through email or telephone and in the past physically) to make deals on the best offers they find. This is a better approximation to the functioning of some real markets, such as derivative, bond markets or the trades that occured in Exchange Alley in 17th century London. In this setting the agent is unaware of all the offers that are being made, simulating a certain degree of uncertainty in the agent's environment. In this model, fundamentalist agents observe a history of dividends of a firm which is updated stochastically and with which it calculates a fundamental value it uses to make its decisions. Once again, this aims to replicate real financial markets where predicting future dividends depends largely on the volatility of the system, and how well it is understood by the agents. This causes serious difficulties in predicting future dividends, giving the possibility of the derived fundamental value to be erroneous. Finally, chartists also present characteristics different from other studies as they use moving averages to extrapolate future estimates of a price.

2 Theory Development

In the late 80s a number of structural asset pricing models began highlight the importance of heterogeneous agents in describing real behavior in agents about their different price expectations. A reason for this change includes the excess volatility in stock prices that could not be explained by the underlying economic fundamentals of homogeneous rational agents (Shiller, 1989). The stock market crash in October 1987 as well as the strong appreciation followed by a sudden depreciation of the dollar in the mid-eighties showed the difficulties in analyzing these phenomena using representative, rational agent models (Frankel & Froot, 1986). As shown by Milgrom and

Stokey (1982), supposing that all agents are rational and know of each other's rationality, there would be no trade. An advantaged agent that has certain information unavailable to others will not be traded with as the other traders will believe there are in disadvantage when trading the stocks he[1] is interested in[2]. The large volume of stocks that are traded daily empirically contrast with these conclusions resulting in a more plausible way to consider markets. That agents are not homogeneous and possibly not all act rationally.

Authors also criticized the unrealistic assumptions about agent's full computational power and perfect knowledge about the environment (Arthur, 1995) (Hommes, 2001). This lead to assumptions regarding bounded rationality instead (Sargent, 1993). Supposing it is not aware of the nature, details and functioning of the model, a bounded rational agent bases his rational expectations upon the data that he observes and updates it each time he perceives new data. Other reasons that lead to a shift between rational homogeneous agent models to models with heterogeneous and bounded rational agents include the increasing popularity and easiness of use of computational tools that have increased the capacity to make simulations (Judd, 2006), empirical proof that agents do not always behave rationally (Taylor & Allen, 1992) and new developments in mathematics, computer science and physics in nonlinear dynamics, chaos and complex systems which encouraged researchers to apply these new concepts to economics and finance (W. Brock, Hsieh, & LeBaron, 1991).

In most cases two types of agents are considered in heterogeneous and bounded rationality models. The first, often referred to as fundamentalists, are bounded rational or rational agents that rely on an individually assigned fundamental values. In some models the agents already have an assigned fundamental value they bet on, while in others they derive it from the expected future returns (dividends) of the companies that emit those stocks. The other type of agent that is often studied (Hoffmann, Delre, Eije, & Jager, 2005) is the trend follower technical analyst or chartist. This agent bases his decision largely on the momentum of the trend of price fluctuations based on simple trading rules, extrapolation of trends and different patterns observed in passed prices. The Friedman hypothesis, elaborated by Milton Friedman (1953), a strong defender of the rational agent approach, argued that non-rational agents would not survive evolutionary competition and would subsequently perform badly in the market up to the point they would be driven out. Empirical evidence points out to the contrary as still today a large number of traders use chartist rules to derive the value of a stock (Taylor & Allen, 1992). This has made researchers question the motives that drive this behavior. Literature in behavioral economics finds various reasons which include a social dimension (Hoffmann et al., 2005), lack of resources to calculate the fundamental value, or the possibility to satisfy the need for substance as following this behavior might allow him to financial returns (Max-Neef, 1992). Chartist behavior appears to be a strong force that drives prices away from a fundamental value while an increase in the number of fundamentalists results in a price approximation to the fundamental value (Hoffmann et al., 2005). What follows is a revision of the characteristics of both types of agents and a review on heterogeneous agent interaction in ABM (Agent based modeling).

2.1 Fundamentalist Agents

A fundamental analysis approach to buying and selling stocks in the financial market relies on the (strong) underlying assumption that each stock has an intrinsic value. The large majority of modern asset pricing models meant to derive this value are founded on the following relationship:

$$P_{i,t} = E_t[M_{(t+1)}X_{(i,t+1)}]$$

Where $P_{i,t}$ is the price of the asset i (its intrinsic value) at time t, M_{t+1} is some stochastic discount factor (SDF) such as the interest rate and $X_{i,t+1}$ which represents the payoff of asset i at time $t+1$. $X_{i,t+1}$ is generally split into a future price component ($P_{i,t+1}$) and future cash flows ($D_{i,t+1}$) which when referring to stocks are normally considered to be dividends. Because $X_{i,t+1}$ is not known with certainty, the SDF is considered to calculate the state-contingent possible payoffs of the stock in t+1 discounting to its present value. Still, even if $D_{i,t+1}$ are known with certainty,

[1] For matters of convenience and common use I use the masculine form. Changing it to the female form is equally acceptable throughout the essay.

[2] Note that these results do not contradict the efficient market hypothesis (EMH) where all information is reflected in the market price and is available to all traders.

both the SDF and future interest rates are unpredictable and depend on factors such as economic circumstances in the environment (Geiger, 2011).

When referring to stocks, this expression is commonly specified as follows:

$$Value\ of\ Stock = (Div_1)/(1+r)^1 + (Div_2)/(1+r)^2 + \cdots + (Div_n)/(1+r)^n$$

Where Div_n are the dividends that the holder expects the company to emit in future period n. This method of calculating the returns of the investment compares the valued asset with the minimum periodic percentage that the investor hopes to earn by investing in the stock he is valuing r. This discount rate also includes the level of risk and uncertainty the trader faces.

A specific case where this model is applied is when the growth of a company is expected to be continuous. That is, with growing dividends in perpetuity. This method is called the Gordon Growth Model:

$$Value\ of\ Stock = Div_1/(r_e - g)$$

Where Div_1 is equal to the dividends that the investor expects to receive one year from the present. r_e is the required rate of return for equity investors and g is the constant growth rate in perpetuity that is expected for the dividends.

If market efficiency is considered, rational and homogeneous behavior of economic agents such as agents calculating their perfect marginal utility are given, the price of a stock will always reach the fundamental value[3] (Chandra & Thenmozhi, 2017). Fundamentalists rely on these assumptions and attempt to capitalize on assets that are overpriced and under priced. In other words, they buy a stock when its calculated fundamental value is above the price at which it is traded on the market and sell when it is below. The difference between both is the profit that is expected to be made (Lee, 1987). These gains remain as long it takes for the new information to be incorporated into the market (Graham & Dodd, 1962).

For the fundamentalist approach to be most effective, costs of acquiring and manipulating information must be minimized. When the costs of collecting and making use of a certain type of information is high, it could have a greater effect on the costs of valuating the stock than on its market price (given assumptions of the market equilibrium condition). As such, the net monetary gain from using a specific piece of information is not larger than its cost (Lee, 1987) (Stiglitz, 1980). For this reason, fundamentalists are considered to have (or rather, required to have) superior analytical skill in deducting conclusions from given information. They also tend to rely on an expanded and elaborate network that gives them an advantage in accessing information (Hoffmann et al., 2005). It is only when information costs are reduced, the fundamentalist approach is effective.

Although fundamental analysis is widely considered and applied, research has shown that prices do not always reflect fundamental values and that the stock market can present fluctuating behavior (Bernard & Thomas, 1990). This puts in question the assumptions made by fundamentalists. An example of such market phenomena are the emergence of bubbles, subsequent crashes and other financial frenzies and panics (Youssefmir, Huberman, & Hogg, 1998) (Tedeschi, Lori, & Gallegati, 2012). Borges (2010) published an article where he tested the EMH with data of various European countries from 1993 until 2007 and concluded that while evidence supported the hypothesis for some countries, it was rejected by others. This lead to debate on whether the efficient market hypothesis is rejected by the data or not.

The assumption that agents are homogeneous and rational is often rejected by behavioral economics and seems to be more often applied to reach theoretical conclusions than in real life scenarios. The heterogeneity of the agents depends on many factors. For example, while studying the heterogeneity in household expectations from the Michigan Survey of Consumers, it was found that the number of people who believed that it was a good time to buy a house due to rising prices doubled towards the end of the boom (Piazzesi & Schneider, 2009). The fundamentalist approach, thus undermines the importance of the effect social influence has on financial markets. An example of this is the tendency to imitate others, which is further elaborated in the section regarding chartists. A reason which might induce heterogeneity is the degree of uncertainty that exists in the financial environment. The knowledge of the environmental circumstances and computing

[3] These conclusions have been challenged by a line of literature that determines that bubbles can form, even under conditions of rationality. For more on this refer to Blanchard and Watson (1982). In order to describe the litarature I base the fundamentalist agent on, I follow the previous line of literature.

capacity of individuals is limited. Coupled with the difficulties and costs to acquire new, valuable information necessary to make perfect rational and optimal decisions, investors are argued to be rationally bounded (Sargent, 1993). This means that under the resulting uncertainty agents make decisions based on satisfying rules of thumb (Herbert, 1957). This uncertainty coupled with debate on what variables should be considered while deriving the intrinsic value of an asset, gives space for investor sentiment and market psychology to play an important role in financial markets (Keynes, 1936).

Generally, as fundamentalists invest in favor of the fundamental value they estimate, they tend to bring prices close to the fundamental value (Chandra & Thenmozhi, 2017). These investors draw their expected value of the company and the stock from a series of relatively simple rules and empirical data. When they hold similar information, there are only small differences in the price they are willing to pay for a stock (Franke & Westerhoff, 2014).

2.2 Chartist Agents

Chartists, also referred to as technical analysts, base their expectations about future asset prices and their trading strategies on observed patterns in past prices. By doing so they attempt to extrapolate price patterns and make their trading decisions accordingly. In a survey made to hedge fund managers, Taylor and Allen (1992), found that over 90% of respondents used different varieties of technical analysis to predict returns to some degree. Menkhoff (2010) also found more recent evidence defending the widespread use of chartist behavior in fund management internationally. Compared to fundamentalists, chartist agents have less capacity to compute the fundamental value, due to high costs of accessing and processing information (Stiglitz, 1980) or the lack of a network where they can access the previous (Hoffmann et al., 2005). Bandura and Walters (1963) define two processes through which a child adopts attitudes, values and patterns of social behavior. In the first, referred to as instrumental training, socializing agents (such as parents), are explicit about what they wish the child to learn and encourage that using punishments or rewards. The second also the one through which the child acquires most of the knowledge he uses in the future, remarks the importance of learning through the imitation of the behavior and attitude of the socializing agent. Shiller (1984) argued that imitation is not only crucial in the learning process of a child, but also in the behavior of individuals in social life as well as in financial markets. Considering that decisions of others are based on a variety of sources of information, imitation can represent a fully rational form of behavior (Shiller, 1984). The (possibly rational) tendency of traders to imitate each other's decisions mark important patterns in price movements and trading behaviors in financial markets (Hirshleifer & Teoh, 2009). One important factor that affects this tendency is uncertainty and the interconnectivity of different traders. When an agent does not have enough information available to make an optimal decision, it could base its actions on that of others (Cialdini & Goldstein, 2004). As an agent begins to form part of social groups, it may be inclined to imitate the behavior of other people in the network (Janssen & Jager, 2003).

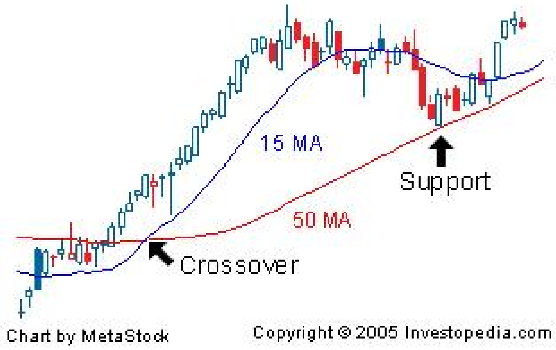
There are several chartist strategies that have been elaborated in the literature and which are practiced by real life traders. Due to the numerous assumptions based on human behavior, it is oversimplifying to assume that only one form of chartist exists, making it necessary to have an extensive literature dedicated to describing possible chartist forms of behavior that can be observed given different circumstances. The popularity of a certain strategy can also depend on other social or environmental causes. The following are just a few of the strategies adopted by chartists in the literature and employed by real traders in the stock market.

2.2.1 Moving average (MA) trading rules

A study performed by Taylor and Allen (1992) concluded that among the different trading strategies adopted by chartists, moving average rules (MA) are the most common. There are various varieties and they are all based on the concept of MA, an indicator that filters out noise of past random price fluctuations and helps identify a trend direction and to recognize resistance levels. A common practice is calculating a short term MA, comparing it to a long term MA and recognizing when both trends cross. By doing so, chartists can identify a momentum shift and changes in prices that are likely to occur. In this case, a buy signal is given when short term MA crosses above the long term MA.

The larger the MA, the less susceptible it is to fluctuations. Therefore they are perceived as being useful in determining momentum shifts.

Figure 1: MA crossover – Source:Investopedia.com



Other chartist trading rules include the close observation of chart patterns paying special attention to certain indicators such as Heads and Shoulders (Figure 2) and Cups and Handles (Figure 3).

2.2.2 Head and Shoulders

Head and Shoulders (HS) and Inverse Head and Shoulders (IHS) indicate chartists a likely reversal of the trend. A HS can be recognized by three peaks, the middle one being the highest (head) and the other two topping at roughly equal levels (shoulders). The lows that join the different points are considered as support levels that indicate a breakdown and a trend reversal. The IHS on the other hand, indicates an upcoming upwards trend, following the opposite pattern as the HS. Lo, Mamaysky, and Wang (2000) developed the following algorithmic detection of head and shoulder patterns. HS and IHS patterns are characterized by a sequence of five local extrema $E_1, \ldots E_5$ such that:

$$HS \equiv \left\{ \begin{array}{c} E_1\, is\, a\, maximum \\ E_3 > E_1,\ E_3 > E_5 \\ E_1\, and\, E_5\, are\, within\, 1.5\, percent\, of\, their\, average \\ E_2\, and\, E_4\, are\, within\, 1.5\, percent\, of\, their\, average \end{array} \right\}$$

$$IHS \equiv \left\{ \begin{array}{c} E_1\, is\, a\, minimum \\ E_3 < E_1,\ E_3 < E_5 \\ E_1\, and\, E_5\, arewithin\, 1.5\, percent\, of\, their\, average \\ E_2\, and\, E_4\, are\, within\, 1.5\, percent\, of\, their\, average \end{array} \right\}$$

The importance of the five extrema is because when looking for HS, there are three peaks that one must search for; the middle one being the largest. Since consecutive extrema need to alternate between maxima and minima for smooth functions, there needs to be five local extrema: a maximum, a minimum, a highest maximum, a minimum and a maximum. In other words, for two consecutive maxima to be local maxima, there must also be local minimum in between. The contrary happens for two consecutive minima.

2.2.3 Double Tops and Bottoms:

After a long growth or decline of a price, if its value hits a support or resistance level twice without going past, chartists believe that the Double Top (DP) or Bottom (DB) indicates a reversal in the trend. Once again, Lo et al. (2000) developed the following algorithmic detection of DP and DB patterns.

To identify a DT, start at a local maximum E_1. From here I identify the highest local maximum E_a that occurs after E_1 in the set of all local extrema in the sample. These two tops E_1 and E_a must be within 1.5% of their average. These tops must be set at least 22 trading days (1 month) apart. To identify a DB, a similar process is taken but searching for minima instead of maxima. To express this mathematically, consider an initial local extremum E_1 and subsequent local extrema E_a and E_b as well as time t_k^* and price at time t_k^*, P_{tk}^* such that:

$$E_a \equiv sup\{P_{tk}^* : t_k^* > t_1^*, k = 2, ..., n\}$$

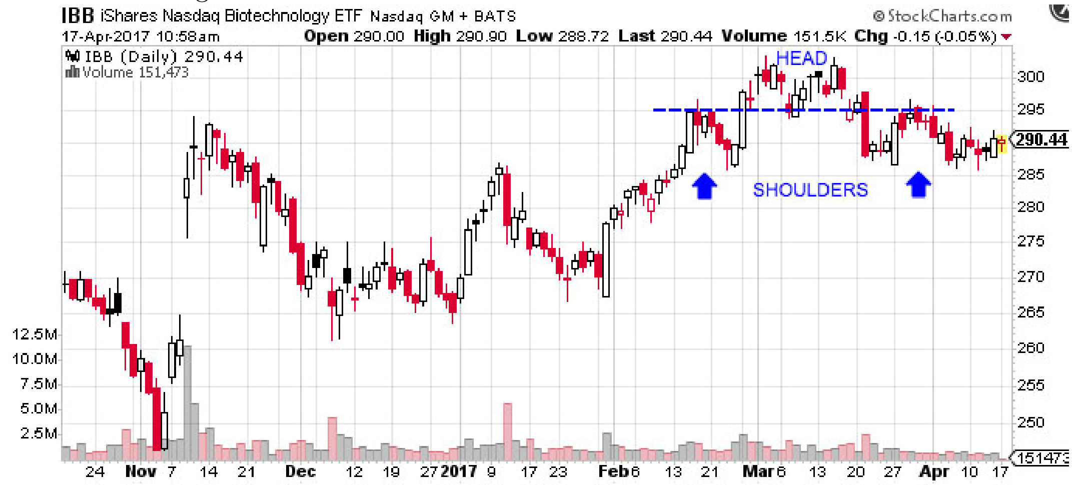


Figure 2: Head and Shoulders – Source:StockCharts.com

$$E_b \equiv inf\{P^*_{tk} : t^*_k > t^*_1, k = 2, ..., n\}$$

And

$$DT \equiv \left\{ \begin{array}{c} E_1\, is\, a\, maximum \\ E_1\, and\, E_a\, are\, within\, 1.5\, percent\, of\, their\, average \\ t^*_a - t^*_1 > 22 \end{array} \right\}$$

$$DB \equiv \left\{ \begin{array}{c} E_1\, is\, a\, minimum \\ E_1\, and\, E_b\, are\, within\, 1.5\, percent\, of\, their\, average \\ t^*_a - t^*_1 > 22 \end{array} \right\}$$

Figure 3: Double Tops and Bottoms – Source:StockCharts.com

Chartist trading rules are considered to be unstable and some researchers even dismiss this approach as being as scientific as astrology (Malkiel, 1996). The debate on whether it is a profitable strategy to invest through a chartist strategy was largely incited by a paper by W. Brock, Lakinishok, and LeBaron (1992) where it is shown that simple trading rules return statistically as well as economically significant profits. As a response, there were a number of articles that showed that these conclusions were limited. LeBaron (1999) showed that by adding the data that corresponded to the following 10 years to sample used by B. Brock and Hommes (1998)(B. Brock & Hommes, 1999), the once best performing trading rule (150 day MA rule) resulted in severe losses the next decade. Ready (1997) had previously concluded that the MA rules used by Brock returned positive revenues only in the 60s.

Due to the widespread use of chartist behavior, one may question if this strategy succeeds simply due to a self-fulfilling prophecy and not because of a scientific reasoning that explains chart patterns as caused by the nature of the stock, which would indeed be comparable to astrology. Agents that participate in a financial market most likely act according to the recommendations of studies regarding it. This problem is not shared by other complex systems such as studies in physics. In a market, if a large number of traders has similar expectations on the future value of a price, their expectations are more likely to be fulfilled as this is the price they are willing to trade a stock for in the market. Garzarelli, Cristelli, Pompa, Zaccaria, and Pietronero (2014), find evidence that memory effects in price dynamics are associated with resistance and support figures and that prices are more likely to bounce at this prices than cross them. Such a study shows evidence of the existence of the self-reinforcement of agents' beliefs and sentiments about future stock price behavior.

In ABM literature, chartists commonly cause the price of the stock to deviate from its fundamental value as they do not consider the value of the firms projected dividends. Instead, they base their expected value on other factors such as social influences (Hoffmann et al., 2005). When the ratio between both agents is kept small, the fundamentalist agents manage provide a strong enough force in the market to bring the price towards the fundamental value. This force is disrupted once the C-F ratio reaches a tipping point where the chartists have a larger influence on the market price driving prices away from the fundamental value (Hoffmann et al., 2005)(Beja & Goldman, 1980).

2.3 Agent Based Models

The use of agent based models (ABM) allows researchers to study complex systems and to determine conclusions on phenomena such as emergent behavior or resilience. As such, ABMs have taken an important role in recent literature regarding the stock market (Mandes & Winker, 2015). ABMs simulate the interaction of individual heterogeneous agents to determine the behavior of systems. This contrasts with "top down" approaches which make assumptions on the resulting effect of the interactions between agents. Often homogeneity is assumed within agents in order to reach this goal. Both approaches present different strengths and weaknesses. The following is a review of the strengths and weaknesses of ABM as put by Turrel (2016).

- *Emergent Behavior:* ABMs are recognized for having the capacity of simulating bottom up behavior based on the interactions of individual, heterogeneous agents to produce macroscopic behavior. A relevant example is Adam Smith's metaphor for the invisible hand which is made visible when applying ABM.

- *Heterogeneity:* As individual agents are considered, it is possible to study the effects of heterogeneity in agents. This is ideal to study different types of traders such as chartists and fundamentalists, assigning different values for the agents to determine to what degree these strategies influence their behavior.

- *Realistic Behaviors:* Given the observed behavior it is possible to generate realistic behavior which can be manipulated. This property has proven useful to include the concepts of behavioral economics such as bounded rationality.

- *Exploring Possibilities:* through ABM it is possible to study a large number of possibilities considering different properties of agents and their environment. Using probabilistic rules applied to individual agents is a simpler way of considering scenarios than working out how the entire population should behave together.

- *Complexity, non-linearity and multiple equilibria:* ABMs are often used to study complex systems which are characterized by having a number of interconnected parts, variables that suffer dramatic changes and which show self-organization. In addition, simulation results vary radically when the assumptions that are made differ. Still there is much debate over how to model the financial stock market and what assumptions should be made (Mandes & Winker, 2015).

ABMs also show certain weaknesses. The following is a summary of these as put by Turrel (2016):

- *Lucas Critique:* This critique states that predicting the concequences of an economic policy entirely on the basis of relationships observed in historical data is naive. Since the parameters of social models change once the policy is applied, conclusions that disregard these changes could be erroneous (Lucas, 1976). Jager and Edmonds (2015) state that predicting and parameterizing agents to achieve an emergent behavior that resembles historical data can be conflicting. This data corresponds with the scenario that in the end happened and not the number of possibilities that did not occur due, often due to random probability. They also argue that the ability to explore different scenarios with ABM is necessary for the understanding of the implications of a policy.

- *Simple Models:* ABMs can design agents that respond to changes in their environment so that they always follow an optimal course of action but this comes at the cost of designing simple and understandable models. This presents ABMs with a trade of between including the intricate details of reality and offering simple models. This makes the conclusions derived from the models to be highly dependent on this trade off.

- *Difficulties Generalizing:* Due to the necessity of adopting assumptions that might be very specific to a certain environment (e.g. the housing market), it is difficult to extrapolate the conclusions made to other circumstances (e.g. stock market).

- *Calibration and interpretation:* When creating a model, it is necessary to assign values to some variables to fit the known facts. The way to verify these values is through comparing the results obtained with the model with historical data. If a model has a large number of options on how it is built it can reproduce data that would seem similar to empirical data, yet does not address the same variables that occur in reality.

Due to the capacity of ABMs to include heterogeneous agents, they are often used to study the effect of chartists and fundamentalists on stock prices. One of the first studies concerning this topic assumed linear trading rules for each type of trading. The conclusion showed that when the fraction of chartists is sufficiently high, the system falls out of equilibrium (Beja & Goldman, 1980). This model was modified by Chiarella (1992) who instead made trend following nonlinear showing that when the fraction of chartists to fundamentalists was higher than a certain value, equilibrium was replaced by a limit cycle. Under this value, the system remained in equilibrium. The excess demand of the different agents also changed as the cycle traversed which led to variations from the equilibrium price. Similar conclusions are reached in Hoffmann et al. (2005) where special emphasis is put on the social needs that make agents adopt a chartist strategy.

Lux and Marchesi (1999) and B. Brock and Hommes (1997)(B. Brock & Hommes, 1998)(B. Brock & Hommes, 1999), instead worked with models that allow for endogenous changes in the agents' strategies between chartist and fundamentalist. B. Brock and Hommes (1997)(B. Brock & Hommes, 1998)(B. Brock & Hommes, 1999) put special emphasis on bifurcation structure and conditions under which price trends are chaotic, making assumptions on market clearing. On the other hand, Lux and Marchesi (1999) use a disequilibrium method of price formation and focus on creating a model that simulates similar behavior of observed markets. They put special emphasis on the market as a signal processor and assume a stochastic value process. As is further elaborated in the next section, the ABM used to conduct this study is more similar to the first as there is no endogenous formation of agents. This was decided due to a will to focus the effect of each type of agent and to maintain the simplicity of the model. It should nevertheless be acknowledged that this limitation should be revised in future studies in order to model agents that are more realistic as they are willing to change their strategy if it does not return positive profits.

Given the importance of heterogeneous agents in the stock market and the capacity to study their emergent interactions using ABMs, this study focuses on the following: The effect that the ratio of chartist to fundamentalists has on stock price volatility in the market. This study allows us not only to allow the agents to interact in a new way but also to make conclusions about the self-fulfilling prophecy that allows chartists to flourish.

3 Methodology

I use ABM due to a preexisting belief that market fluctuations are caused by agent heterogeneity. This tool enables us to simulate market volatility and price formation that form out of states in the market which are initially in equilibrium. ABM provides the means necessary to study emergent behavior typical of complex systems. Because much has already been written regarding this topic (refer to section 2.), this study has relied on an ABM which has certain characteristics which distinguishes it from the rest as will be elaborated shortly. This ABM has been constructed using Python 3 by a team of students of the University of Groningen lead by Ph.D candidate J.A. Schasfoort.

3.1 The Model

In order to provide a concise and effective description of the model, I follow the ODD as elaborated by Grimm et al. (2010). It is a cornerstone in ABM development as it lays guidelines to make ODD descriptions more comprehensible and complete. Simultaneously, it allows ABM to be standardized and less susceptible to criticism for being irreproducible. The acronym stands for the main components that describe any ABM: Overview, Design concepts and Details (ODD). These are used as sections in the following description where each section is split into its different components by enumerating them. This is done in order to make the description of the model clearer for the reader.

3.1.1 Overview

(#1.1 Purpose) The aim of this study is to draw conclusions on whether the C-F ratio has an impact on price formation in a financial stock market. *(#1.2 Entities, State and variables)* The model is composed of the following entities, each with their state variables and parameters that characterizes them:

Firm: The firm has a certain book value based on its assets and liabilities. The profits it makes follows a random exogenous process. It keeps a profit history by storing all previous profits. These profits are turned into dividends at a determined dividend rate. For the purposes of this study, only one firm is considered therefore all investors trade the stocks of the same firm. The model begins with an initial public offering by the firm where it offers a set number of stocks for a determined price (both established as initial parameters). After this, the agents trade these stocks among themselves.

Traders: All traders begin with a determined budget with which they buy stocks emitted by the firm. Each agent is characterized for having an interval of past data they choose to derive the expected dividend in the next period (fundamentalists) or the moving average, used to extrapolate an expected price trend, of the prices the trader traded the stock for in the past (chartists). There are two types of agents; chartists and fundamentalists, each with their respective strategies. As the model starts with a total of 100 agents and is run for a number of C-F ratios, each run will have a different number of each type depending on the C-F ratio.

Stock portfolio: The stock portfolio is another variable that characterizes the agents, marking the number of stocks of the single firm an agent owns at a certain period in time.

Firm Stocks: Each period, the average previous stock price which depends on the transactions made by the agents on the stock is stored. There is a certain amount of each stock in circulation.

(*#1.3 Process overview and scheduling*) These entities interact each quarter through the following process:

1. The firms update their profits and dividends.
2. Given historical data and each traders strategy they update their prices and spread.
3. Traders are matched arbitrarily in a random order with a group of other traders with whom they have the option to trade with. The fact that the matching process is arbitrary is a design decision motivated by a will to maintain the model simple[4]. Each trader trades on the best offers it receives; buying if it considers an offered stock to be under valued and selling if it considers is over valued. This market mechanism is known as “over the counter” (OTC) market mechanism and does not rely on a centralized trading mechanism that is commonly used in other studies. For this reason, our model does not require the common use of market makers or dealer to collect all bids and asks, set a price and then match the

[4]This limitation should be reviewed as it discards network effects that one might see in real life OTC markets where each trader seeks out those agents he has had better offers from from the past.

different traders. OTCs are considered to be opaque as the traders only have knowledge of the trading conditions that are being offered to each one (Duffie, 2012). This market mechanism is still employed today in the derivative and bond markets. Because the realistic observable set size for each agent and the total number of agents in these markets is too high to allow the model to run efficiently given a time constraint, the employment of this model can be better described with London's Exchange Alley as in the 17th and 18th centuries. This alley commonly served as a shortcut between the Post Office and the Royal Exchange. As such, the coffee shops that were located in it became centers for lively trading of shares and commodities. Traders would come to these coffee shops and shout their bids and offers which would be heard by those nearby who would respond with their own offers until a deal was reached. This center marks the beginning of the modern London Stock Exchange. An illustrative example of this is Lloyd's Coffee house which would later become the well-known Lloyd's Bank (Shillingford, 2014). In addition to the interesting perspective of this approach, OTC allowed the authors to simplify the construction of the model. Nevertheless this can be considered another limitation of the model as it does not reflect modern day markets.

4. The last step that is taken is updating the market prices the traders traded for this turn. There is not a single market price but instead, each agent has its own collection of past deals. By making good deals where the trader sells the stock for more than what it was bought, he earns money which it will reinvest if it finds a suitable offer according to its valuation of the stock in future turns.

3.1.2 Design Concepts

(#2.1 Basic Principles) The foundations of this model are based on concepts of asset pricing theory and behavioral economics. Fundamentalists rely on the Gordon Growth Model, making a net present calculation of the value of a stock based on dividends. Chartists, on the other hand, rely more on concepts of behavioral economics. They rely on the concepts of MA. Each chartist calculates two different moving averages, one being longer than the other. They then compare them and extrapolate the future price of the stock based on the change they have gone through, deriving a value. Another concept that highlights the design of this ABM is the use of an OTC market mechanism which is iconic in some markets such as the currency or derivative markets.

(#2.3 Emergence) The interactions between agents will lead to bottom up effects on the price, the volume and the frequency stocks are traded at. *(#2.4 Adaptation)* Given these effects, agents adapt their expectations based on their memory of previous dividends (fundamentalists) and market prices (chartists). It is important to pinpoint a possible improvement in the model in this case, as limiting the fundamentalists capacity of deriving the value of stocks by just observing the history of the dividends ignores the forward looking capacity of these agents to evaluate firms when profits are expected to change (given for example the development of a project). This fundamentalist quality should be reviewed in future research. Once expectations are adapted, agents determine new stock values and the quantity that each wants to buy or sell of each stock. The action of buying or selling occurs once two agents that are matched consider each other's offer beneficial given the expected value that each has for given stock. *(#2.5 Objectives)* The main aim of each trader is to buy stocks that are priced below their expected value and sell at a price that is above. *(#2.6 Learning)* The agents do not adapt their strategies with gained experience. If one strategy results as superior to the other, an agent does not change to that winning strategy, therefore there is not a real learning process in the agents. This is a limitation that should be elaborated on in future updates of the model. *(#2.7 Prediction)* The strategies that each type of agent uses to predict the value of the stock differs. Fundamentalists predict dividends based on extrapolating a set of previous dividend values. Since the actual dividend process is stochastic, they might be erroneous in their prediction. Chartists on the other hand extrapolate past trends using MA, this implies that although a stock has an upwards/downwards trend, the agent will not overpay/undersell it. *(#2.8 Interaction)* Agents interact through an OTC market mechanism where they are given the option to trade with those traders they are matched with every period. They only take the action of selling or buying if they find an offer which they believe they benefit from given their valuation of the stock. This entails that agents face uncertainty of being aware of only the offers that are being made to them. *(#2.9 Stochasticity)* Random numbers are used in the initialization, the dividend process and while setting up the market mechanism. In the first, they are required to randomly distribute the agent state variables in a range. During the dividend process, as the actual value of

the dividend is stochastic. And lastly, in the market mechanism as the order that the agents enter and leave the market is random. In order to ensure stochasticity, the Mersienne Twister Number Generator from the Python random package is applied. *(#2.10 Collectives)* At initialization, agents are split into two groups: Fundamentalists and Chartists. After this, the only alternative action for an agent is to not act. This occurs when it's budget runs out. *(#2.11 Observation)* All object state variables as well as the transactions that take place in the market are collected when at the end of each period. Those variables that show emergent behavior and that are of special interest to this study are the prices, the quantities and the frequency of transactions.

3.1.3 Details

(*#3.1 Initialization*) Apart from the ratio of chartists to fundamentalists and the total number of agents, initial variables are fixed within a range. This range is not based on data. Stocks are initially distributed at random. As a pseudo random number generator is used, models can be exactly replicated when using a fixed seed. (*#3.2 Input Data*) The model does not use input from external sources such as data files or other models to represent processes that change over time. The following are the values used at initialization:

- **Seed = 0**: I use this parameter to control the random number generator. In other words, when the seed is equal to 0, a different set of random numbers will be generated than when the seed is set to 1. In this case, to control for randomness and to be able to replicate the experiments, a single seed which is arbitrarily assigned the value 0 is used.

- **Simulation time = 100**: Because of time, the model cannot run indefinitely as a realistic stock model would. For this reason, the sequence runs 100 times as during this period of time, the emergent properties of the model arise.

- **Amount of Agents = 100**: The total number of agents is small due to efforts to make the model efficient when running. Yet, this may not be seen as a large deviation from the hypothetical number of people that can fit in a coffee shop at a given time. Although, modern OTC markets would require a larger number of agents as well as a larger number of agents a trader can contact each period given the use of modern technology such as emails and telephones, the number used in this study is reduced to 100 agents in order to allow the model to run more efficiently. Further research where the effect of this variable is elaborated on is recommended.

- **Ratio of Fundamentalists/Chartists = (0, 0.5, 0.1, ..., 1)**: As this is the main variable of interest, the simulation runs 21 times as this will show not only the different effects that result from agent interaction but also how these effects evolve as the ratio changes. A singular realistic ratio of chartists to fundamentalists cannot be identified as it largely depends on external factors such as uncertainty and network connectivity and will continuously vary.

- **Amount of Firms = 1**: As risk perception has not yet been integrated in the model, the portfolios that would be created would deviate from what one might expect in a real scenario. In addition to this, minimizing the amount of firms allows us to focus our attention to the properties that emerge given changes in our independent variable. Possible future studies could research the effect of this variable given different numbers of firms.

- **Initial money = (100, 200)**: The initial amount of money available to the traders is largely arbitrary and was chosen in a way that would allow the agents to interact. Still, a certain degree of inequality has been added in order to ensure deeper heterogeneity among agents.

- **Dividend Memory (3,7)**: Fundamentalists determine the value of a stock by discounting the average of a certain number of the dividends that were issued by the firm in the past. The memory of these agents determines the number of dividends he considers to calculate the average. In this paper, fundamentalists can observe between 3 and 7 past dividends given that at the initialization he is assigned a certain memory in this range. This allows for heterogeneity also among the fundamentalists. Because fundamentalists are not capable of assigning a greater weight to more recent data points, a larger memory would assign too little importance to more recent prices. For this reason it is recommendable to use a smaller set of data points the fundamentalists look back on than what real fundamentalists would consider.

- **Memory MA (1,3)**: When more data points are employed to construct the MA, this measure becomes more lagged and thus more conservative. For the purposes of this study, the number of points used to calculate the MA is minimized in a way that noise is reduced yet the agents are still strongly inclined to follow trends. Another reason to not use many points to calculate this value is that the small number of agents will not provide with as much noise as is expected in a real financial market where millions of trades exist. This could make noise in an OTC setting in a London cafe, a less important factor than in a present financial market.

- **Initial Profit = (200), Initial Book value (10000)**: These variables are highly dependent of each other as one cannot expect a firm with a low book value to have high initial profits. As these values highly depend on the type of firm and industry that is studied, the values have been assigned in such a way that there is sufficient trade volume to obtain conclusive results.

- **Initial stock amount = (400)**: For efficiency purposes, this value is smaller than what might be expected in a real stock market. Still, it is large enough that trade volume can be analyzed and that certain stock values might deviate a lot from each other. The total number of stocks stays constant throughout time as the traders only trade among themselves.

- **Observable set size (5)**: This value is considered in a setting where a number of traders are in a cafe attempting to grab each other's attention to find the best offer. In this setting, one can assume that, due to the noise and other distractions, including a possible overflow of information, each trader can only attract the attention of a few other traders who are in their immediate proximities. It is hard to give an exact value to this variable, but under this reasoning, one could find 5 to be a justified value.

(*#3.3 Submodels*) There are three submodels that are necessary for the model to run: A fundamentalist and a chartist algorithm for the expected value of the stock and the market matching process.

Fundamentalist Algorithm: Fundamentalists act according to a calculated fundamental value which is dependent on the dividend rate and the expected dividends. The algorithm through which their values are calculated is the following:

$$FV = \frac{Div}{r}$$

Where FV is the fundamental value that an agent calculates for a stock, Div is average value of past dividends the agents remember (Dividend Memory), the $r = 0.05$ is the discount rate. This model is comparable to the Gordon Growth Model where the growth rate is equal to zero. Using this value, the fundamentalist buys the stock if one of the traders it is matched with on a certain period offers to sell the stock for lower than the fundamentalists estimated FV, sells if it is higher and holds if both hold the same value.

Although the use of this algorithm allows the model to remain simple, it also presents difficulties that should be addressed in future updates in the model. If one would consider fundamentalists to be rational agents, this would imply that it has an understanding on what factors affect the performance of the firm and act in a way where, given this knowledge, would act in its best interest. Given that the performance of the firm is stochastic in the model, the expected dividend of the next period is random. That is, the next dividend will randomly deviate a certain degree from the previous. In this study, a rational agent would not consider a perpetual discount dividend model as it is aware that this holds no relation with the firms performance. Modeling fundamentalists in such a way would imply that they are irrational. A necessary future development to overcome this issue is to model the firms in such a way where their performance is no longer stochastic or to remodel the agents to construct their expected value aware that the firm performance is stochastic.

Chartist Algorithm: Chartists base their strategies upon their observed trends in the stock market. To do so, they use MA. Each chartist has a different approach to the time interval used to calculate them. The value they are willing to buy/sell a stock is based on an extrapolation from the change between them. This can be represented using the following expression:

$$CV = MA_t + (\frac{s}{2} + 0.5) * (MA_t - MA_{t-1})$$

Where CV is the chartist estimated value of a stock, s is the number of points used to calculate both MA. MA_t the present value of the stock without considering the noise factor which is eliminated using the MA. MA_{t-1} is the value that the chartist calculated the period before using the same number of data points as in MA_t. $(\frac{s}{2} + 0.5) * (MA_t - MA_{t-1})$ is the predicted growth that is expected to occur in the next period.

Market Matching Process: On the first turn, the stocks are distributed randomly among the agents. As the simulation begins, the traders are mixed randomly. Next, for each trader, it is given a random subset of traders and their ask price. The trader selects the cheapest trader from that set and proceeds to buy the maximum amount of stocks possible from that trader, given his budget. In order to increase trading volume, the put and call price for the stocks of each agent is equal to its expected value of that stock. As the agent derives this value, he is indifferent on holding the stock or its value in cash. Therefore, a price offered above this expected value will be a more profitable option for the agent which will result in its sale. A parallel argument can be made to explain the motives behind buying a stock when an offer is made for lower than the agent's expected value.

3.2 The Analysis

Using the model, a database was created collecting the values of the variables for 21 different ratios of chartists to fundamentalists $(0/100, 5/95, ...)$. Preliminary conclusions were be made by studying this database and seeing how different price patterns emerged. The variable of special interest for this study is the prices the stocks are traded for throughout time. To allow for a better analysis of the evolution of the stocks price, emphasis is given to the average price the stock is traded by all traders each turn through time. It is important to signal that the results are also dependent on the performance of the firm. As this variable is random in our model, deductions can be made only from given firm performances. In other words, our results will not be analyzed for controlled performances of the firm. These conclusions will be elaborated on in the following section and the resulting patterns will try to be explained through theories of complexity science, asset pricing and behavioral economics.

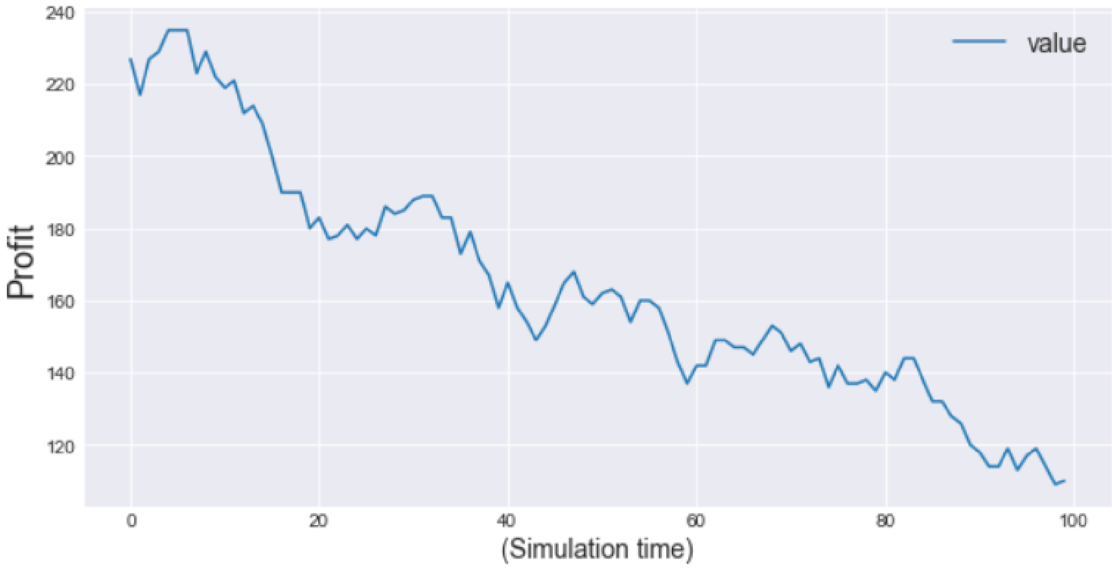
4 Results

The following collects and elaborates on the results obtained from the previously described model. I begin by describing the baseline model dynamics studying the different states the model reaches and how this occurs. I discuss the results for the following chartist/fundamentalist ratios: 0/100, 85/15 and 30/70. The reason the extreme case where all agents are chartists is not considered is because the way the model is set up results in the chartists not being able to extrapolate a trend at the initialization. The ratio 30/70 is payed special attention to as it symbolizes a tipping point where the effects of both agents are dominant at different stages of the model, yet also largely affected. It is also important and crucial to note that the simulation where the results of this thesis are elaborated on derive from an arbitrary simulated firm whose profits declined through time as can be seen in Figure 4. This random outcome has a significant impact in the results as will be elaborated on shorty. If one would consider the results in a scenario where the firm issues larger dividends through time, one could find a parallel explanation to the one explained in this thesis.

4.1 Model Dynamics

Once the simulation starts, two distinct phases are seen to emerge: the price grows steadily until the simulation ends or the following of the agents estimated price with the depreciation of the firm caused by a decrease in the value of its emitted dividends. As will be noted, the results of the 30/70 ratio are singular as it represents a tipping point in the formation of stock prices. To illustrate this phenomena, the formation of stock prices based on the agents expectations is studied.

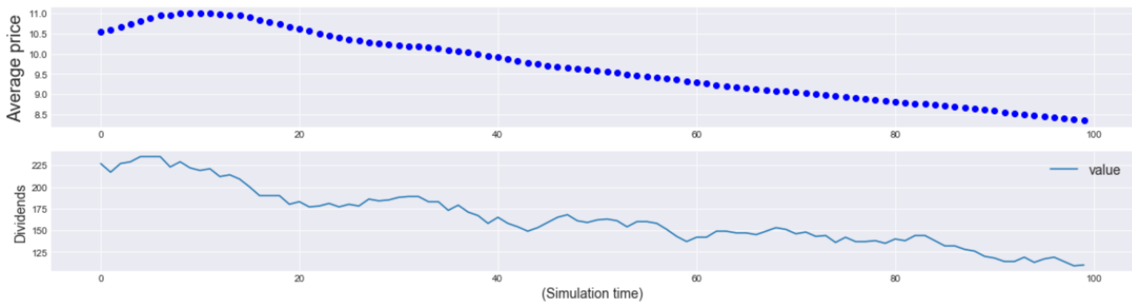
Figure 4: Dividends through simulated time



4.1.1 The 0/100 Ratio

This scenario is fully dominated by fundamentalist agents. This extreme scenario would occur when the costs of acquiring and manipulating the information required to calculate the value of the firm are low. This is because for the fundamentalist approach to be effective, therefore attractive for traders, the costs of deriving the fundamental value must be smaller than the gross profits that the trader is expected to make by trading stocks (Lee, 1987). An additional cause that can lead to a fundamentalist dominated scenario can be an environment where the traders all believe that the stock price reflects the value of the firm and have enough information to derive with certainty this value. When these factors are present, the fundamentalists pay close attention to the evolution of the dividends and are only willing to trade for prices close to this value. This can be illustrated in Figure 5.

Figure 5: Fundamentalist formulated price and firm dividends through time.



It can be seen how at the initialization, there is a small drop in the value of the emitted dividends followed shortly by an increase. The fundamentalist agents, in an attempt to discard any noise factors average out the value of the past 3 to 7 dividends and do not have a large consideration for the value of this small drop as well as future small volatility. As the value of dividends increase, fundamentalists are willing to pay more leading to a small increase up to period 8. The subsequent crash of the firms profits leads the fundamentalists to trade the stock for less money.

This emergent phenomena, where the expected prices the agents formulate follows the value of the dividend can be seen through all the states where the fundamentalists drive stock prices (0/100-25/75). This occurs when the proportion of fundamentalists is significantly larger than that of chartists. It is worth noting that as more chartists are considered in these fundamentalist dominated scenarios, the more will the expected price deviate from the dividend value, even if the general tendency is to follow this value.

4.1.2 The 85/15 ratio

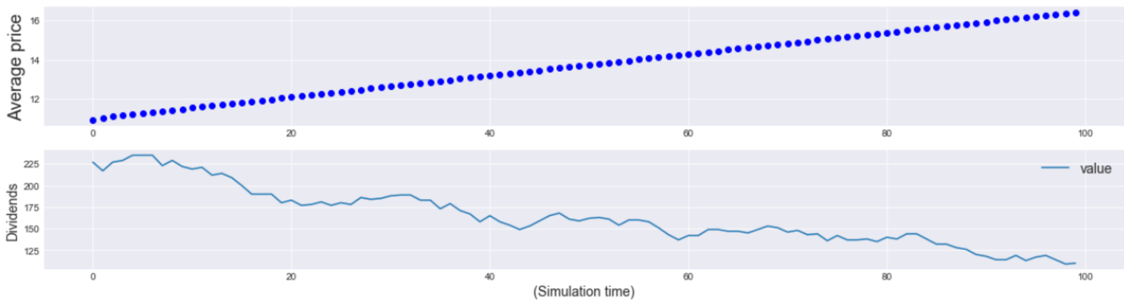
As was noted previously, this model cannot initially run in a scenario where there are no fundamentalists since chartists agents need some initial offered price to calculate a trend. For this reason, this is the highest calculated ratio of chartist to fundamentalists that was considered in this paper. In a real world where the concept of initialization is not considered, a scenario with only chartists would result in an accentuation of the following results.

A scenario where agents follow predominantly chartist strategies can be caused by a high degree of uncertainty in the market. Since agents are not capable of obtaining enough information to make an estimated value of the firm, they imitate the actions of other investors that do act in hopes that the process through which they make their decisions is well based. Considering that other traders are based on a variety of sources of information, imitation can represent a fully rational behavior (Shiller, 1984). An example where an event could cause an increase in the degree of uncertainty could be political negotiations over new policies that could affect the firms' performance.

Another way to explain an increasing popularity for chartist behavior is by considering a setting where although a trader believes that the dividend reflects the state of the firm and can calculate it cheaply, he is surrounded by coworkers that do not spend as much time and money calculating the fundamental value of a stock and yet, as this strategy can be considered self fulfilling, obtain higher yields. This trader might be aware that the stock is largely overvalued but still decides to buy it because of this social pressure where he sees that the many people he relates with are making abnormal gains.

In Figure 6 this is further elaborated.

Figure 6: Chartist dominated scenario formulated price and firm dividends through time.



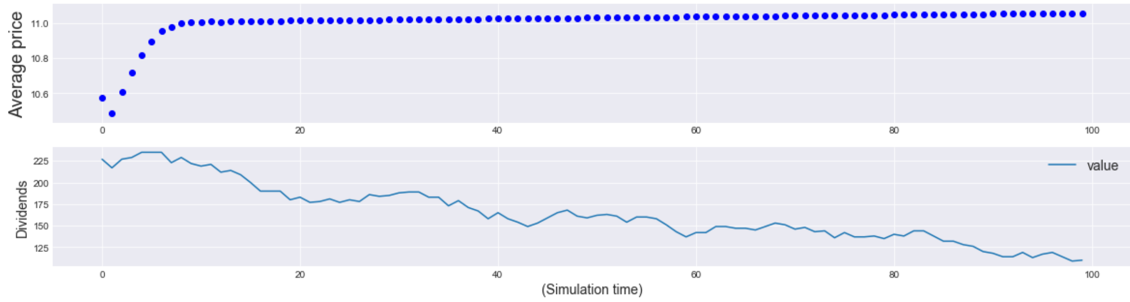
Because chartists consider an average of past prices to calculate their expected price, they depend on some initial trades with fundamentalists. Once they have enough data to calculate the trend, they begin trading in the market, extrapolating the moving averages trend of the prices traded among the fundamentalists.

Because traders are aware that the information they are not aware of will highly influence the stock price, it is rational to follow the decisions of others as they consider themselves to have enough information to make such a move. Because traders are only aware of the decisions of other traders and not the motivations behind these actions, they assume that those who act have enough information to do so. As they do not have access to this information they will follow others, causing (in this case) the stock to be perpetually overvalued.

4.1.3 The 30/70 ratio

This ratio is of special interest because it represents a tipping point between both states discussed previously. As can be noted in Figure 7, there is a first phase where chartist behavior strongly dominates by inflating the price above the dividend calculated fundamental value. Given that the fundamentalists find good trading deals with the chartists for a stock they consider is not performing well after period 8, they sell all their stock. This is followed by a drastic decrease in the growth of the average price of the stock until the point where the trend continues growing, although much slower, close to the value of $11,00\$$. As the fundamentalists no longer buy since they consider the stock to be overvalued, they are driven out of the market. This explains that although the value of the dividends continues to decrease, this has no impact in the expected price of the agents.

Figure 7: Tipping point scenario formulated price and firm dividends through time.



5 Conclusions and Final Observations

In this paper a financial complexity model is applied to the question of price formation given agent heterogeneity in a financial market. A firm that issued dividends given its profits is simulated and analyzed how, depending on the ratio of different types of agents, were expected prices formed.

A unique feature of this model if compared with other work is the use of an OTC market where agents meet physically and trade, limiting the number of traders one can make their offers to. Another singularity of this research is the use of moving averages used by chartists to calculate an expected value of the stock. Given this set up, the formation of stock prices of a firm and how they deviated or followed the fundamental value was studied. When the fraction of chartists was large enough, prices would deviate perpetually and when fundamentalists dominate the market, the price would follow the value of the dividends. An interesting observation which indicates a tipping point between the dominance of one strategy over the other is the case where due to the fundamentalists selling all their stock, the price trend decreases.

Areas of future research in the subject of agent heterogeneity on stock formation using this model, includes studying the effects of the other variables. The results that have been postulated in this paper can only be conclusive once a thorough understanding of all the models properties is gained. Possible future research could include the effect that the total number of agents has on price volatility or the interactions between types of agents given various firms.

Still, it is important to note a number of limitations many of which are result of maintaining the model's simplicity. Some of these limitations can be reviewed in future research updating the model.

The first and perhaps most relevant characteristic of the model which could limit the results of this paper is the use of a firm that generates random profits. Although real life firms are not expected to perpetually grow, they do confirm to profit patterns that characterize them, such as industry they belong to or their size. Because fundamentalists attempt to derive expectations without considering this crucial detail, it is not possible to confirm that these agents are rational, not confirming with the literature on what a fundamentalist is. A way to improve on this error is to model the firm to be more realistic and then model the fundamentalist in a way that it is aware of the firms profit formation rules.

Another limitation of this work is the exclusion of endogenous changes in the C-F ratio. It would be expected that changes in the price would imply changes in the agents environment. This in turn would incentivize agents to adapt their strategy. Agents can also change their strategies if they observe that their current approach does not have positive returns as compared to that of other agents. This addition would add a form of networking effect that is currently lacking.

In a wish to replicate agent heterogeneity, two behavior models were designed. Reality is much more complicated than that and further heterogeneity should be added in order to correctly describe real markets. An example of this would be including additional chartist rules such as the head and shoulders or double top markers or the inclusion of risk awareness which could make an agent less willing to pay a high price for a very risky stock.

Finally, this research should be expanded on including a larger number of seeds an comparing the effects on market prices given different firm performances. Although while conducting the research that resulted in this thesis, I saw parallel observations with different firm performances, these should be included in a paper of larger extent in the future.

Agent based models still have a long way to go before they have an imminent impact in policy making and research. This is due to the increasingly fast and complex way stock markets are evolving, making it difficult for researchers to model these changes in a way that they are resilient to the Lucas Critique. Yet it points out to a need of ABM to grow and adapt to modern markets as only then can policy makers base their decisions on the results that derive from these models.

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