The Internet as source of herding behavior: Exploring consequences in financial markets

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Abstract

By interconnecting traders' strategies through the price of a risky asset, this paper constructs a causal structure that is the base of a system dynamics simulation model about an artificial financial market. At first, the market is free of herding behavior. However, the market becomes contaminated by the inflow of individual investors who trade with strategies designed by others. Individual investors imitate traders that get the best trading performances and the way to obtain it is from the Internet. By comparing the simulation results of the markets with and without herding, we investigate the impact of herding on the market liquidity and on the traders' performances. Our findings show that although herding generates illiquidity and volatility, it is not a decisive factor to determine which traders perform better. However, the wealth of these traders could be harmed when the individual investors trade in the market.

Keywords: Financial Market, Herding behavior, Illiquidity, System Dynamics, Simulation.

Introduction

Information is vital to trade in any financial market. With the appropriate information, a trader can have a better edge in her investments by reducing both risks and potential losses. Vlastakis and Markellos (2012) agree with that stance and assert that information is the most valuable and highly sought asset in financial markets. Traders search for information in different ways: the interaction with other traders or colleagues (Panchenko, Gerasymchuk and Pavlov (2013)), the media reports (Tetlok (2007)), expert opinions, etc. Nowadays, however, the Internet is becoming the prime source of financial information (Mondria, Wu and Zhang (2010), Da, Engelberg and Gao (2011), Vlastakis et al.). There are several reasons for that: finance websites can provide live information on any asset anywhere anytime, their access is easy, fast, convenient and economical. Those aspects justify why these websites are used so frequently: Finance.yahoo.com was visited by 186 M in December, 2014; Fidelity.com by 29.2 M in the same month; Moneycontrol.com by 26.5 M, from data provided by www.similarweb.com.

Picking up information from the Internet to trade in any financial market should have positive consequences for individual investors since they become more informed (Rubin and Rubin (2010)) and, consequently, they can aspire to achieve a better performance. However, these users could also undervalue the risk (Barber and Odean (2001), Nosic and Weber (2010)) and adopt trading behaviors that might affect their outcome negatively (Barber and Odean (2000)). But not only there are individual consequences. The widespread use of the Internet might encourage multiple investors to adopt the same trading strategy. This decision, whether it is planned or not, could cause either the emergence of herding in the market or the intensification of its presence if the market already suffers from it (Hirshleifer, Subrahmanyam and Titman (1994)). Herding, understood as the behavior of investors that ignore their own information and adopt strategies designed by others, is an important source of financial distress for markets (Iori and Tedeschi (2010), Tedeschi, Iori and Galleati (2012), Gebka and Wohar (2013)). Indeed, Bikhchandani and Sharma (2000) claim that herding can destabilize markets, lead to inefficiency, causes excess volatility, increases the fragility of financial systems, and induces systemic risk.

Although herding is a global phenomenon, not all financial markets evidence it in the same degree. Literature attributes this fact to several factors. Galariotis, Rong and Spyrou (2015) point out the influence of institutional rules in markets and estimate that herding increases during economic crisis or when fundamental information is released. Gebka et al., indicate that mature markets undergo less herding than markets in emerging countries. Simões and Valente (2015) suggest that the degree of financial sophistication in the market influences herding volume. Specifically, these authors remark that herding is scarce in big and developed markets whereas it is abundant in small and illiquid markets. This hypothesis is based on diverse studies that detect herding among investors in different countries (Choe, Kho and Stulz (1999) for South Korea, Voronkova and Bohl (2005) for Poland, Wylie (2005) for the UK, Simões and Valente for Portugal, Walter and Weber (2006) for Germany). Nevertheless, it seems important to notice that the level of herding in the markets is difficult to confirm due to the conflictive results that appears after testing herding intensity by different indicators (Xie, Xu and Zhang (2015)).

These considerations lead us to pose the causality direction between herding and illiquidity. If imitation characterizes herding, a selling position would be followed by a cascade of selling positions that, in a small market, could not to find a clear counter parted. The market would suffer from imbalances between demand and supply that would cause price fluctuations, which becomes common in market affected by herding. Consequently, the market would be perceived as illiquid when really the lack of liquidity is due to the imitation. To test this conjecture, the paper constructs an artificial financial market populated by heterogeneous investors that follow different trading strategies. Therefore, this market is free from herding behavior. However, the market becomes contaminated by the inflow of other individual investors who trade with strategies designed by some one of the first investors, who will be called financial gurus. Without considering the reasons why the new traders behave in this way, these individual investors imitate gurus that get the best trading performances and the way to obtain that information is through Internet. The new market can admit different levels of herding and the analysis of its dynamics allow us to reckon the conjecture.

Our research is related to Akiyama, Hanaki and Ishikawa (2014) regarding the way to address the study: the artificial market replaces a fraction of experienced traders with individual investors without modifying the rest of the conditions. However, unlike these authors, our market contains a higher number of investors that trade following different rules to buy and to sell. Nevertheless, some aspects examined in Akiyama et al., can also be studied by means of our model. In particular, it is possible to study how traders modify their trading strategies when facing individual investors. The introduction of gurus in laboratory models is also considered in Iori et al., Tedeschi et al. and Markose, Alentorn and Krause (2004). As Iori et al. and Tedeschi et al., we explore the variations that wealth's gurus undergo taking into account that the models allow individual investors to change of guru. However, the change criterion is different. Our model contains a mechanism that selects the trader whose wealth verifies a profitability criterion instead of allowing traders to choose the guru with certain probability. Therefore, our selection of gurus assumes that the idea for the flock is not to expect a specific trading result but to expect for the best performance. The selection of gurus also differs from that of Markose et al. in which the gurus do not need to take part in the market. Moreover, unlike all these authors, the bond among investors is not an internal communication structure, but the Internet, which allows new investors to get information continuously regardless of their number and their location. Also, in contrast to the previous studies, the methodological approach selected in this paper focuses on causal links that lead to determine the dynamics of the market as a result of feedback processes. In this manner, the model captures the interconnections among three essential elements in artificial markets: strategies of heterogeneous traders, asset prices and the actions of a market maker.

Although, any financial market can be considered as a dynamic complex system per excellence, system dynamics (SD) methodology is not a common instrument for its analysis. This fact attracts attention since agent based modeling (Martinez-Jaramillo and Tsang (2009)), that shares certain concepts with SD (Scholl (2001)), is more common in financial analysis. The lack of a SD view in the study of financial markets could be caused by at least two factors. The first is related to the influence of exogenous factors on the markets (Fama (1970)), an issue difficult to deal in SD. The second concerns the inherent uncertainty of the markets that financial literature has handled statistically. In spite of these factors, SD could be an alternative methodology to study a financial market after examining how its dynamics could be explained by means of feedback loops. As a result of using SD methodology, the model is mainly determinist and endogenous. Its structure of prices and traders shares many aspects with the models of Lux (1998) and Martinez-Jaramillo et al., but the differences highlight the importance of the methodology to gain insights into issues not fully resolved in finance.

The contribution of this paper is twofold. First, the use of system dynamic methodology to model financial markets is an innovative approach to address the complexity of these markets. In this way, SD literature grows to include the own peculiarities of the financial markets. In particular, the causal structure that describes trading strategies is peculiar. The structure shows the interconnections among traders´ decisions but not only from a relational side, as usual in SD, but also from a temporal perspective. The second contribution is related to the aim pursued by the paper. In this regard, financial literature could gain insights to increase the understanding of the effects of herding behavior. Our research finds results behind herding confirmed by literature such as prices volatility, changes of strategies both in the gurus and in the rest of traders, or the fact that special traders can become gurus in the long run, such as noise traders. However, other results differ of consulted literature: The power law decay of the returns distribution is not especially significant or the wealth of gurus could not improve as a result of herding. Finally, some results are new-fangled: illiquidity is influenced by herding that, in turn, increases prices kurtosis and decreases returns kurtosis.

The rest of paper is organized as follows. The causal structure that explains both the price formation and the trading strategies of the heterogeneous investors is examined in the second section. The third section calibrates the models without herding and checks stylized facts for all them and describes the simulation results. The fourth section introduces individual investors, checks stylized facts and describes the simulation results. We conclude in the fifth section.

The structure of the market

The model assumes that only one risky asset is traded and that the market is a spot market in which no significant event will occur: the number of stocks stays constant; there will not be splits; there will not new capital; the company that issued the asset will survive in the market; etc. The asset price behavior over time is explained endogenously from the interactions between the actions of heterogeneous traders and a market maker. Each trader has a portfolio formed by stocks and cash, which are updated when a market order is placed.

To complete the characterization of the market, the price formation mechanism and the traders' strategies need to be specified.

Price formation

One of the most important issues in the modeling of a financial market is to determine the mechanism of stock price formation. Many methods exist in real markets, but most fit into one of four possibilities that LeBaron (2006) enumerates: order book, market clearing, price adjustment and random matching. The third method uses a process of adjustment that is common in SD: the market maker announces a price and traders can present an offer to buy, or an offer to sell, or can choose to do nothing. Once the offer and supply of each trader is determined, their aggregated values can be calculated. In case the aggregated demand exceeds the aggregated supply, the price goes up a percentage set by the market maker. In contrast, the price decreases a certain percentage, when supply exceeds demand. If there are not orders to buy or/and to sell, the stock price stays unchanged.

Figure 1 shows the causal structure that explains the price formation in a simple market with only two traders. Each trader acts in accordance with its own strategy (that Figure assumes price dependent) adopting one of three alternatives: offers to buy, offers to sell or maintains her position, this is, holds the stocks. The difference between the aggregate bids and the aggregate asks influences the price in the next time step. Nevertheless, the diagram contains more elements directly related to price formation, providing new feedback loops. These new loops account that the aggregate demand and the aggregate supply could be different and the trade could vary less than expected. Moreover, any real buying or any real selling results in a new portfolio.

It must be noticed that the diagram does not include the signs of the causal relationships between the price and the orders because they are unknown. Actually, the sign depends on the decision of each trader and whereas one trader could buy, another one could sell. Also, it must be taken into account that the traders might decide to hold their positions, causing the temporal inexistence of these casual relationships. Certainly, given a trader, if the causal relationship for buying is active, the other one is inactive since the same trader neither buys nor sells at the same time. These characteristics entails that the feedback loops that include that type of causal relationships do not work simultaneously but sequentially and only with certain frequency. During the intervals in which they are active, the causal relationships adopt a sign that does not change. It could be said that these peculiarities adds a temporal complexity to the usual relational complexity of the causal structures constructed with SD.

Heterogeneous traders

It has been found empirically (Bask (2007)) that in the financial markets that could be included in two categories: fundamentalists and technicians or also called chartists or trend followers. Both types of participants use the asset price as an important reference for trading, but a pure fundamentalist and a pure chartist use different signals to buy, sell or maintain the position in the market.

Fundamental traders believe to know the true value of the asset, the fundamental value. To determine that value, they carry out different analysis. They examine the economy in which the asset was issued: GDP, unemployment rate, interest rates, inflation, etc.; they analyze the industry in which the asset takes part: the price levels, the foreign competition, the size, etc., and they also take into account the company that issued the stocks: dividends policy, earnings, cash flow, human resources, etc. Once a fundamental value is determined, the strategy of a fundamentalist is to buy when the asset price is lower than its fundamental value and to sell when the price is higher than that value. This strategy is based on the assumption that sooner or later the asset price will return towards its fundamental value. Figure 2 illustrates the fundamentalist strategy, which is characterized by two negative loops that do not overlapped over time. The fundamental value is an exogenous variable given the established framework for the model.

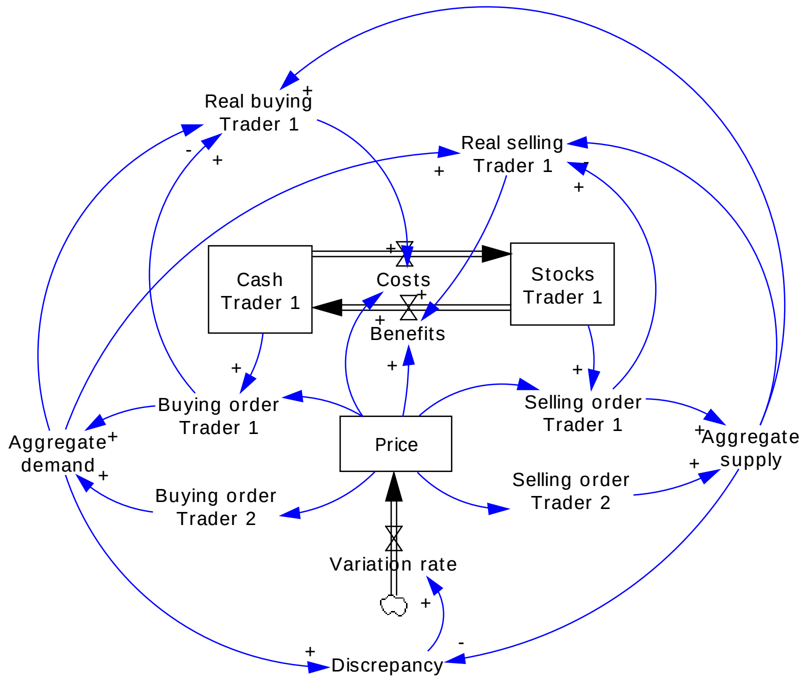

Figure 1: Loops in price formation

The heterogeneity of fundamentalists' traders comes not only from the differences regarding the estimation of the fundamental value but also from the different degrees of tolerance for modifying their positions. A fundamentalist submits orders if the difference between the asset price and the fundamental value exceeds certain threshold, but this threshold is different for each fundamentalist.

Chartist traders pay no attention to economic fundamentals and believe that the future asset prices can be founded by examining its past behavior (Brock and Hommes, 1998). Using past price movements, they construct tables, graphs and indicators looking for trends to make good investment decisions in the market. There are numerous chartist strategies (Kaufman (2013)). This paper considers chartist strategies that have a common feature: their dynamics can be explained by feedback loops in which the price is always a significant element. Figure 2 shows one of them, the popular moving average rule 14:40. A buying (selling) order is placed when the short period moving average rises above (falls below) the medium period moving average and the relation was opposite in previous session. Once again it seems important to observe that the feedback loops that Figure 2 contains do not overlap over time.

Behavioral finance suggests that a market in which only fundamentalists and chartist's traders take part does not explain all behaviors that the real financial markets present, such as bubbles or crashes. Therefore, the markets must contain other many types of traders that use other strategies. Our model considers two new types: positive and negative feedback traders whose strategies depend on the prices trend. Positive feedback traders follow a strategy in accordance with the asset price movement: they buy stocks when the price increases and sell when the price decreases. De Long, Shleifer, Summers and Waldmann (1989) affirm that this strategy is more common that you might think, specially, when portfolio is based on extrapolative expectations. These authors point out that if the volume of these investors is big enough, they can contribute to asset prices diverge from the fundamentals, which undermines fundamentalist's results. Figure 2 also shows the feedback loops that describe the strategy of a positive feedback trader.

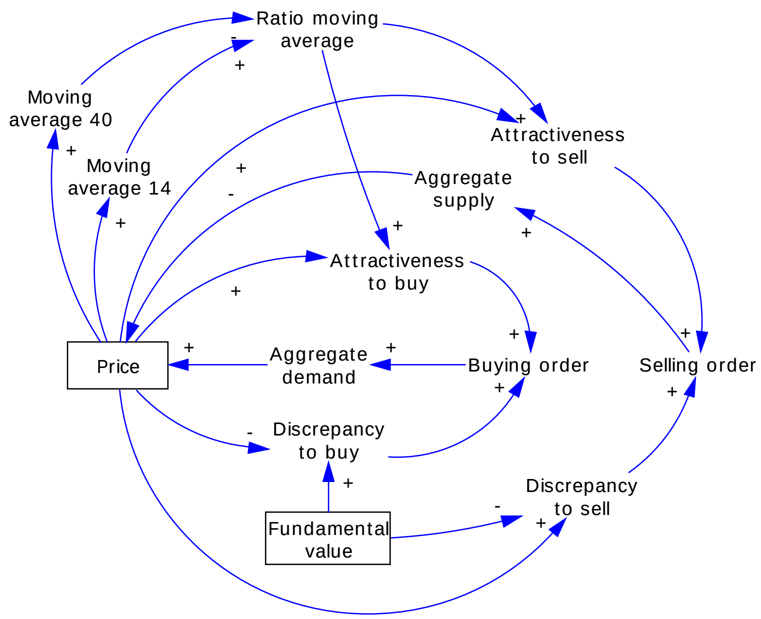

Figure 2: A fundamentalist, a chartists and a positive feedback trader

Likewise, the market could also contain negative feedback traders whose strategy would be led by two negative feedback loops: they buy stocks when the price decreases and sell stocks when the price increases. The strategy is based on expectations: they buy believing that prices have reached their floor and sell believing that the prices have reached its ceiling. The strategies of both positive feedback traders and negative feedback traders could admit different versions. For instance, a positive feedback trader could buy if during a certain temporal horizon the price continuously grows; whereas other trader would require a temporal horizon longer.

Additionally, our market contains noise traders in the style of Ozsoylev, Walden, Yavuz, and Bildik (2014). These traders follow strategies that pay no attention to fundamentals or asset price series but order in terms of probability. As the rest of traders in the market, it is unknown the reasons why invest in this way. The randomness of their strategies might have certain advantages. Individually, noise traders may survive in the long run, even they may gain more money than rational ones (De Long et al.). Collectively, noise traders might have a high participate in the market as consequence of randomness, which enhance the trading volume.

Simulation models

Five models are analyzed. The first model (25-Model) includes 25 trading strategies; the second one (30-Model), contains 30 trading strategies: it adds to 25-Model five new strategies characterized by two indicators as explained below. The rest of the models suffer from herding as they add to these models traders that imitate strategies, who from now on will be Internet traders.

Stylized facts

It must be expected that the models, even when affected by herding, represent financial markets. Then, the markets must exhibit certain stylized facts (Cont, (2001)), which are verified by the asset prices time series regardless of time, asset and market.

To check whether the time series of asset prices obtained from the simulation verifies the stylized facts, the log returns are defined: r(t)=log(P(t)/P(t-1)) [Dimensionless], where P(t) [Euro/Stock] is the asset price at t and P(t-1) at t-1. Seven aspects linked to returns are analyzed: autocorrelations of returns (C(z)=corr(r(t),r(t-z)) where z is the time lag and autocorrelation of absolute returns and its squares. The returns have to present volatility clustering, i.e. high and low volatility tends to cluster. The returns are not Gaussian, the mean is close to zero, they present skewness and they have excess of kurtosis, which reflects that the underlying distribution is non-normal with tail behaviour. After correcting returns for volatility clustering (e.g., via Generalized Auto Regressive Moving Average (GARCH) models), the residual time series still manifest heavy tails.

Algorithm for the price

Setting a temporal horizon T and t=0, the behaviour of price over time can be determined by using an iterative process of four steps:

1. Given an asset price at t, P(t) [$/Stock], each trader according to its strategy selects an alternative: to buy, to sell or to do nothing. At that moment, the portfolio of each trader is C(t) [$] of cash position and S(t) [Stocks] of stocks.
2. If a trader selects to buy, the amount of stocks that it buy is a fraction (g_b) [1/Days] of its cash, this is, it would receive g_b(C(t)/P(t)) [Stocks/Days]. If a trader decides to sell, it would sell a fraction (g_s) [1/Days] of its stocks: g_sS(t) [Stocks/Days]. The aggregate demand (AD(t)=Σg_b C(t)/P(t)) [Stocks/Days] and the aggregate supply (AS(t)=Σg_sS(t)) [Stocks/Days] are the total demand and the total supply of stocks in the market at t.
3. As supply and demand could not to coincide, the exchange of cash and stocks among traders is proportional to aggregate bids and asks; though, both a buyer and a seller will not want to excess its budget. Then, a buyer will obtain MIN{AS(t)/AD(t),1}(g_b C(t)/ P(t)) stocks and its new portfolio will be C(t+1)=C(t)-g_bC(t)MIN{(AS(t)/AD(t),1}, S(t+1)=S(t)+(AS(t)/AD(t))MIN{AS(t)/AD(t),1}.
   Similarly, a seller will sold MIN{AD(t)/AS(t),1}g_sS(t) stocks. The portfolio will be left C(t+1)=C(t)+g_sS(t)P(t) MIN{AS(t)/AD(t),1}, S(t+1)=S(t)-g_sS(t)MIN{AS(t)/AD(t),1}.
4. The market marker sets a new price to reduce the excess demand P(t+1)=P(t)+a(AD(t)-AS(t)), where a [$/Stock/Stock] is the acceleration factor. Now we increase t by a unit and we can go to step 2 if the elapsed time has not reached the final time T.

Traders 'strategies

Determining both the number of traders and their strategies is a hard issue to solve when an artificial financial market is constructed. Any decision is controversial and only the results will decide its appropriateness. This paper considers 30 differenced strategies.

- Four strategies are based on fundamentals. They differ in the thresholds that traders select to buy or to sell and in the fundamental price. There are two fundamental prices that evolve in accordance with a random number that summarizes the uncertainty and the influence of the environment on the market.
- Four strategies are feedback. Two traders follow positive feedback strategies while the other two follow negative feedback ones. The strategies of the couples also differ for the thresholds.
- Four strategies correspond to noise traders. The strategies relate the asset price to a random number.

- Eighteen strategies are chartist's strategies. Ten of these chartists' traders make decisions taking into account an indicator. Two strategies use the simple moving average (SMA): one trader compares SMA(14:40) and the other, SMA(14:40:200). Other trader use the momentum indicator: she buys when P(t) exceeds three or more prices at t-1, t-6, t-30 and t-120. Relative Strength Index (RSI), Bollinger bands, Technical strategy trading range breakout (TRB), Moving Average Convergence Divergence indicator (MACD), Average True Range (ATR) are used by only one trader while the rest follow stochastic oscillators. Therefore, two strategies use indicators of trend, one considers an indicator of volatility and the others follow indicators of momentum. The rest of chartist's strategies combine two indicators: the order is to buy if any suggests that and it is to sell if both indicates that.

The model maintains these strategies during the whole simulation temporal horizon, which not means that a trader has to be in the market or has to maintain always the same strategy. A trader can leave the market or can change of strategy but the strategies will be traded for another one.

Calibration

The temporal horizon is 2.720 trading sessions although the first 200 sessions are discarded to be influenced by the initial values of the delays, which are necessary to evaluate the trading indicators. Therefore, the temporal horizon is ten years (252 trading sessions per year). The unit of time is the day. Three types of calibrations are required: calibration for the market maker, for the asset and fundamental prices and for the traders.

In the market, the initial value of the price is 2 and a proxy for the parameter *a* (fourth step in the algorithm for the price) is the inverse of the traders numbers (Martinez-Jaramillo et al.). When the simulation starts, all traders have the same portfolio C(0)=50 euros, S(0)=50 stocks per trader. Any bid uses 10% of cash (g_b=0.1) and any ask 10% of stocks (g_s=0.1). The fundamental prices are level variables that are initialized with the same initial price value; the associated flows are random numbers that are obtained from a normal distribution with mean null, standard deviation 0.05 and seed 2. The results are obtained from Vensim.

Results

The simulation model contains 616 variables, of which 61 are variable level. The models are dimensionally correct (Rahmandad and Sterman (2012)) and they are robust under extreme situations. The validations entail to check the stylized facts and, in this way, confirm that 25-Model and 30-Model reflect financial markets. Table 1 includes the indicators associated to these analyses. The sections Returns and Prices contain: the mean, skewness, kurtosis, Jarque-Bera test associated to the histogram of returns; the coefficients ARCH and GARCH for a modeling GARCH(1,1) of the returns. The Table also includes results obtained from the asset prices: maximum, minimum, mean, skewness and kurtosis.

More information of this analysis is shown by Figure 3 and 4. The first rows of Figure 3 (25-Model) and Figure 4 (30-Model) illustrate how the asset prices and the returns evolve. These rows also include the histograms of returns. The second rows display the correlograms of returns, absolute returns and squared returns for different time lags, the annualized volatility in returns computed on a period of 40 days and the histogram of standardized residuals after modeling returns by GARCH(1,1). These results together with those showed by Table 1 allow us to confirm that the modeling replicates financial markets. The distribution shape of 25-Model and 30-Model does not coincide with a normal distribution and Jarque-Bera tests are too high, hence it is rejected the null hypothesis whereby the returns are not distributed following a normal distribution. The autocorrelation functions show insignificant values and the returns are uncorrelated. The absolute and the squared returns present correlation, which occur if there is volatility clustering. They display a slowly decaying for various lags. The autocorrelation function of absolute returns has to decay slowly as a function of the time lag, roughly as a power law with an exponent inside the interval [0.2*,* 0.4]. Leptokurtosis is evident. Moreover, the returns and residues histograms contain fat tails. Likewise, both models share that the sum of coefficients ARCH and GARCH is less than one, and then volatility aftershocks will die.

The last row of Figure 3 and Figure 4 illustrate the trading volume, the number of stocks interchanged daily, the differences between the demand and the supply of stocks daily and the prices annualized volatility.

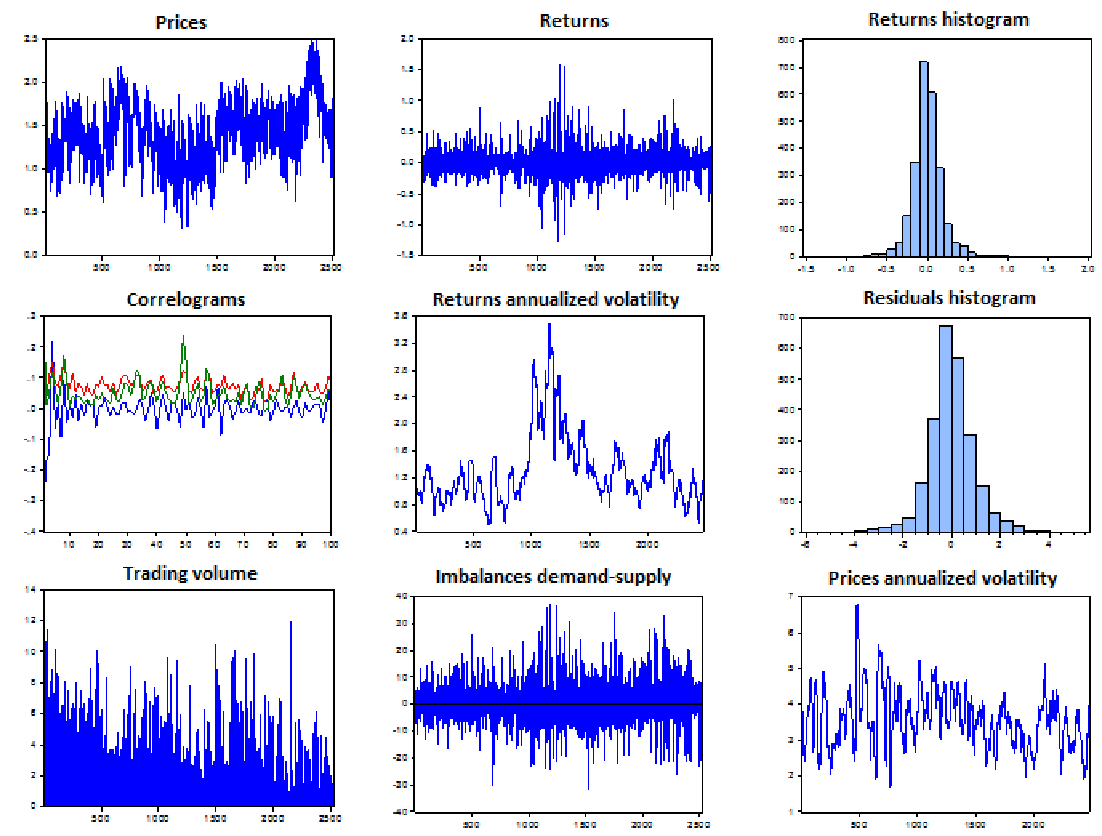

Figure 3: Graphs associated to 25-Model

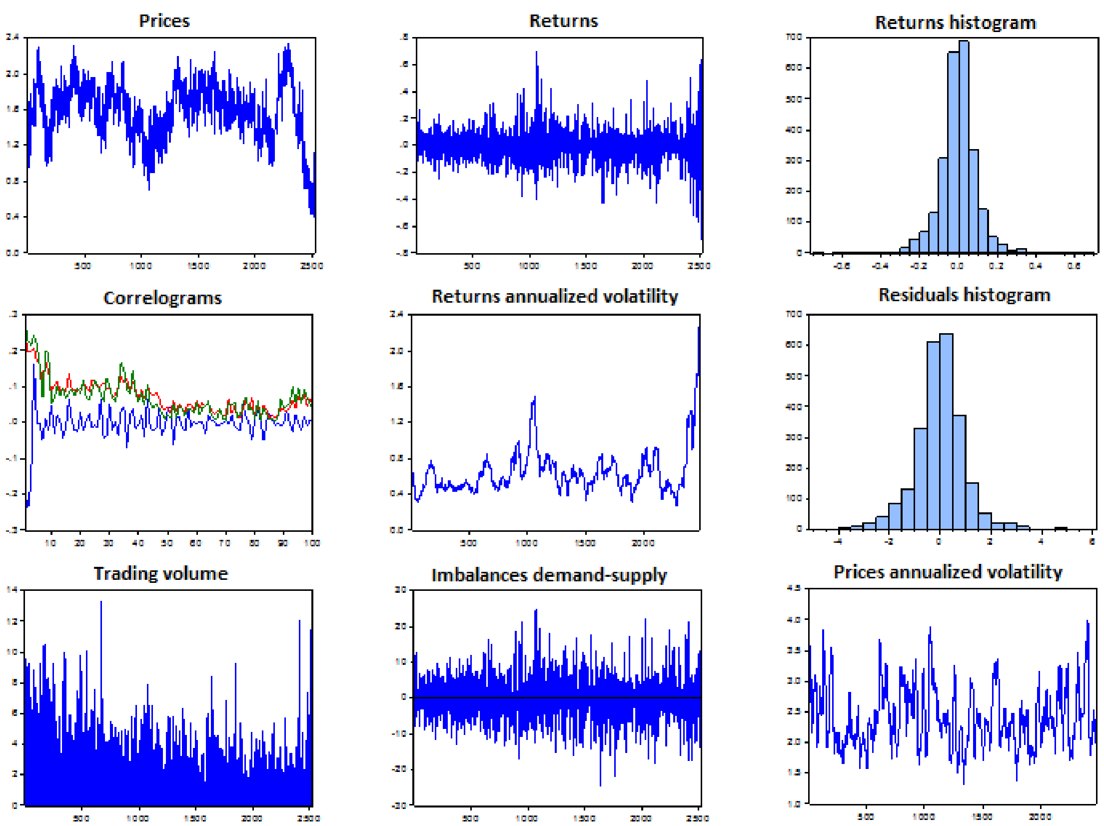

Figure 4: Graphs associated to 30-Model

Including Internet traders

We set up three new markets (25-Model+INT, 25-Model+2INT and 30-Model+INT) that contain Internet traders, therefore these markets are contaminated by herding and it is not necessary to use an indicator to detect it. The 25-Model+INT adds five of these traders to 25-Model; 25-Model+2INT adds a total of ten Internet traders to 25-Model. Finally, the 30-Model+INT adds five Internet traders to 30-Model. Then, 25-Model+INT (25-Model+2INT) has the same number of traders as 30-Model (30-Model+INT).

The Internet traders follow the strategy of that trader that, at each moment, has the best performance (the guru). The new models maintain all characteristics of their predecessors except for the price acceleration factor, which is adjusted in function of traders' number. All Internet traders are added to the models when the simulation starts. Their portfolios are formed exclusively by cash with the same amount as the rest of traders at this moment. The three Internet models have success explaining stylized facts. Table 1 also contains the disaggregated results for these models. Additionally, it also includes other indicators that allow us to obtain more results: the means of returns and prices annualized volatility, the trading volume, the daily average difference between the demand and the supply of stocks, the average of surplus demand and surplus supply as well as the number of days when these situations emerge. The last row of Table 1 shows the percentage of days when different traders are gurus during the whole temporal horizon, and the second percentage refers to the last 252 days of the temporal horizon.

	25-Model	**25-Model+INT**	**25-Model+2INT**	**30-Model**	**30-Model+INT**
Returns					
Mean	-0.000148	-0.000229	-7.38e-05	-0.000409	7.17e-06
Skewness	0.549778	1.315335	0.479740	0.016011	1.391193
Kurtosis	10.55779	11.72641	12.24568	10.24769	10.32671
Jarque-Bera	6124.572(0)	8722.415(0)	9072.331(0)	5520.024(0)	6449.342(0)
GARCH(1,1)					
RESID(-1)^2	0.035983	0.803265	0.031148	0.050068	0.270950
GARCH(-1)	0.953956	0.099039	0.960736	0.933808	0.666368
Annualized volatility (mean)	1.305812	1.811864	1.412924	0.640166	1.670614
Prices					
Mean	1.402354	1.321051	1.591332	1.578866	1.576384
Maximum	2.479700	3.562880	2.516009	2.331150	4.085755
Minimum	0.312420	0.293703	0.156142	0.394800	0.237493
Swekness	0.185723	0.199061	-0.494034	-0.707831	0.138131
Kurtosis	3.065396	2.991678	2.739328	3.982884	3.643788
Annualized volatility (mean)	3.598094	6.477939	4.456797	2.410762	4.510137
Trading volume					
Mean	1.873755	2.243553	1.394280	2.099150	2.339481
Maximum	11.90906	16.07237	13.59290	13.30706	16.21511
Minimum	0.00000	2.52e-11	0.00000	0.00000	0.00000
Days between [0,5)	92.23%	88.66%	93.57%	92.79%	87.58%
Imbalances demand-supply					
Mean	0.008177	-0.0107879	-0.004533	-0.013032	0.004973
Maximum	37.06542	113.721344	82.084358	24.88097	153.930511
Minimum	-31.62659	-37.043964	-44.943256	-24.72145	-31.919807
Surplus demand					
Mean	5.476605	8.196318	5.407276	3.464778	13.818604
Days	1191	1225	1712	1283	1144
Surplus supply					
Mean	-4.919739	-7.768276	-11.456966	-3.611445	-11.471274
Days	1330	1296	809	1240	1377
Gurus[1] (days during the whole temporal horizon and during the last 252 days)	5(89%-93%) 12 (6%-0%) 16 (3%-0%) 2 (2%-7%)	27 (82%-96%) 16 (10%-4%) 26 (5%-0%) 5 (3%-0%)	27 (56%-100%) 26 (38%-0%) 16 (5%-0%) 2 (1%-0%)	27 (82%-96%) 16 (10%-4%) 26 (5%-0%) 5 (3%-0%)	27 (69%-100%) 12 (20%-0%) 16(7%-0%), 5 (2%-0%), 19 (2%-0%)

Table 1: Indicators associated to the models. [1]Numbers 2, 26 and 27 are fundamentalists; 5 and 16 are contrarian traders; 12 is a noise trader and 19 is a trend follower following a stochastic indicator.

Kurtosis

It can be noticed that price and return kurtosis are affected by competitiveness and herding behaviour. Return kurtosis decreases when the market is more competitive and it does not have herding (25-Model faces 30-Model), but the result is reversed if price kurtosis is examined. However, the models with Internet traders have higher return kurtosis than their predecessor (25-Model+INT faces 25-Model, 25-Model+2INT faces 25-Model, 30-Model+INT faces 30-Model) but, once again, the results are reversed if price kurtosis are studied. Moreover, if herding intensity increases, returns kurtosis increases and price kurtosis reduces (25-Model+INT faces 25-Model+2INT). Therefore, kurtosis behind herding behaves opposite for prices and for returns.

Volatility

Through the daily results provided by the model, the annualized volatility for prices and returns is evaluated. Price and return volatility present certain similitudes with the behaviour of price and return kurtosis though the results are not totally parallel. On average, volatility in return and price decreases with competitiveness and without herding (25-Model faces 30-Model). However, the return and price volatility increases with herding if it is compared to the predecessor model (25-Model+INT faces 25-Model, 25-Model+2INT faces 25-Model, 30-Model+INT faces 30-Model). Likewise, if herding intensity increases, then volatility decreases slightly (25-Model+INT faces 25-Model+2INT). The influence of herding on the price and return volatility had already been pointed by Di Guilmi, He and Li (2014).

Power law

In spite of the clear behaviour of kurtosis, the influence on power law related to slow decay of autocorrelation in absolute returns is not significant in models with different herding intensity (see Figure 5, third row). This result differs from that obtained by Di Guilmi et al. that handle a financial market as expectation feedback systems (Heemeijer, Hommes, Sonnemans and Tuinstra, (2006)). The number of traders in our artificial financial market could also be influencing this result as chartists could be offset and fundamentals could dominate the market (Hommes, (2005)).

Trading volume

The trading volume is very similar in both the 25-Model and the 30-Model. Both models show that 99.72% of days are traded between five and ten stocks. However, the influence of herding on trading volume is not clear on average. Whereas the mean, the maximum and the level of activity increases as the number of traders increase, the increase of individual investors do not provoke the same result as the 25-Model+2INT shows (see Figure 5, fifth row). Therefore, once again, the results show the non-linear character of the influences.

Liquidity

By observing (Table 1) the mean of the imbalances between demand and supply, it can be argued that the result depends more on the number of traders than on the intensity of herding. The excess of demand (maximum imbalance) decreases with competitiveness and without herding and increases with herding but the 25-Model+2INT show the non-linear character of the increase. On the other hand, the excess of supply (minimum imbalance) show the opposite behavior with competitiveness and without herding. Herding behavior reduces these values.

Liquidity, defined as the ability to buy or to sell easily, could be characterized by the volume of demand and offer unrealized (surplus demand (mean)*days + abs(surplus supply (mean))*days). In accordance with this indicator, if 25-Model and 30-Model are compared, the former is more illiquid both from the demand side and from the supply side; consequently, it is more illiquid from both sides. Therefore, without herding, competiveness improves the liquidity. With herding the markets are more illiquid regardless they are examined from the surplus of demand. A classification, from more liquid to less liquid, would be: 30-Model, 25-Model, 25-Model+2INT, 25-Model+INT, 30-Model+INT. The classification makes evident that the growth of the unrealized volume is not proportional to herding intensity, implying a non-linear relationship. These results can also be corroborated when the imbalances are compared year by year: the means yearly verify the same condition.

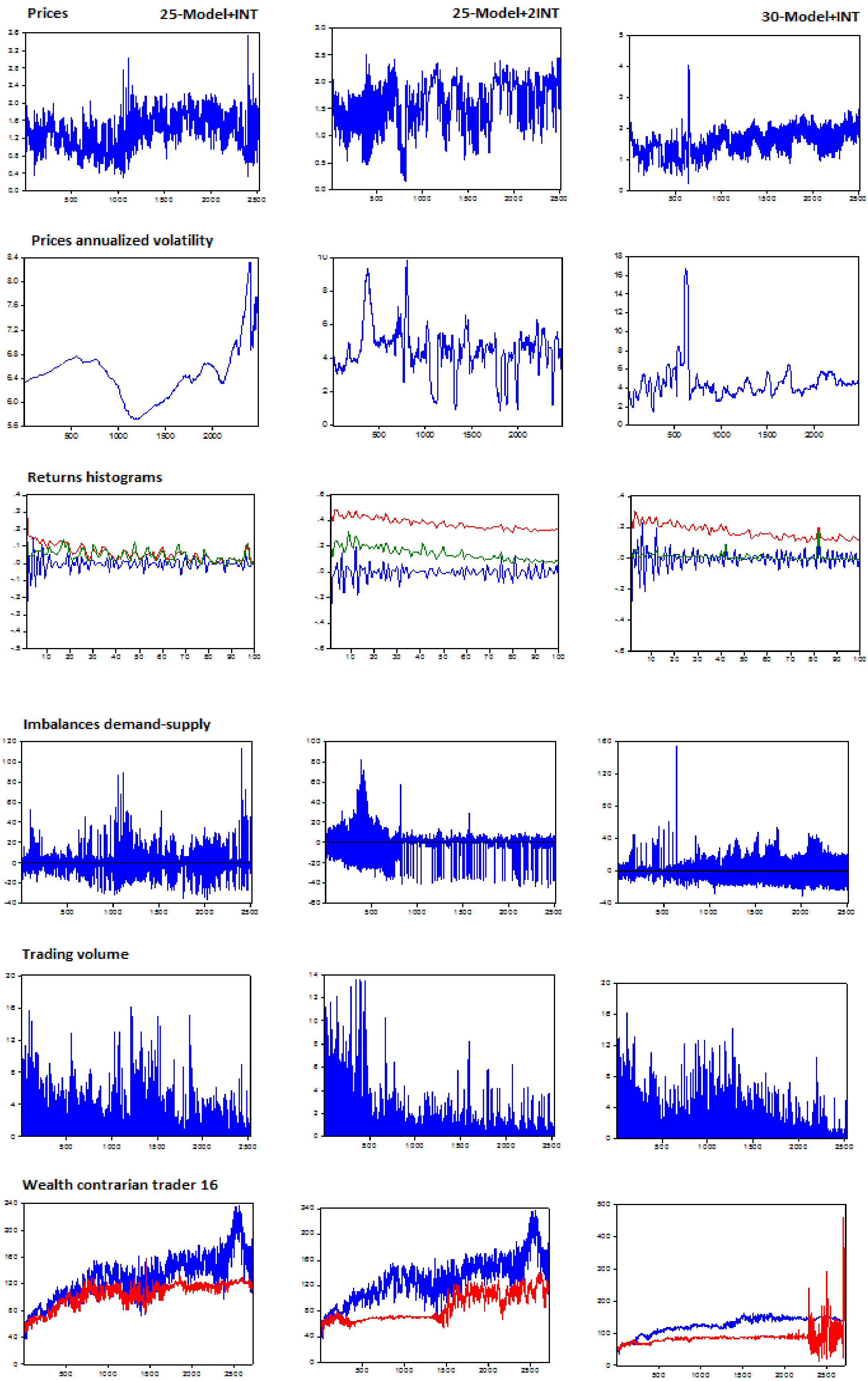

Figure 5: Graphs of models with herding behavior

Traders

Figures 3, 4 and 5 (first row) display the evolution over time of the asset prices in the five models. The different evolution guarantees that experienced traders react, in each model, in different way in spite of following the same rule. The experienced trader that gets the maximum performance changes over time and they also differ among the models. Last row in Table 1 checks that. However, herding does not seem an important factor for experienced traders in order to become elite: some traders are gurus in models without herding (contrarian traders' numbers 5 and 16) and in models with herding as well. Likewise, herding does not seem to influence whether the guru is a fundamentalist or a trend follower. Really, just once a trend follower becomes the guru and this happens in a model with herding.

Fundamentalists become leaders in all markets. This fact contrasts with certain results in literature (Tedeschi et al., De Long et al.) that suggest that herding behavior, contrarian traders, feedback traders or noise traders can lead prices away from fundamentals. However, the result is more aligned to Akiyama et al. who suggest that inexperienced traders could accommodate their trading behavior to follow fundamentals. Nevertheless, the constant presence of fundamentalists in the long run is not clear. As we can see in Table 1, fundamentalists and contrarian traders (5 and 2 for 25-Model, 27 and 16 for 25-Model+INT and 25-Model+2INT) became gurus the last year. This fact is more a feature of the last year that an own characteristic of models type 25. The rest of years show clearly how gurus rotate. Indeed, all the traders that have been related to each model will become gurus in the future.

Performances

Table 1 (last row) shows the rise and fall of gurus over time. This issue has already studied by Tedeschi et al., but in contrast to them our study shows different results. In our case, the gurus should not want to be imitated because, unlike the aforementioned authors, it is not profitably for them. Actually, the wealth of a guru could be higher in models without herding than in models with herding. This result can be checked in Figure 5 (sixth row; blue line correspond to models without herding) that displays the wealth of the contrarian trader number 16, who is a guru in all models.

Last comments

Herding is a difficult phenomenon: it is hard to measure, to detect and to determine its effects. Generally, the findings obtained in laboratories are not totally extrapolated. The results are sensitive to internal conditions (rules imposed by the market maker, rules adopted by the traders, etc.) in addition to methodological aspects. The system dynamics model that we have constructed is based on causal structures: traders act because of price movements that, in turn, they generate. The structure does not change over time because in the market, matter as happens, there will be traders willing to follow a specific strategy. The market always contains the same type of strategies without considering if people who trade are the same individuals or not. This stance differs from other methodological approaches that construct financial markets from structures that evolve over time. Models very often contain some aspects related to learning, allowing traders to learn over time. These differences would justify why the results of our model show different findings than others; a fact that rather than being a setback is a clear evidence of the underlying complexity of financial markets.

The model does not consider the Internet as an excuse to herd. It is the medium that connects different investors who physically can be anywhere in the world. The assumption of the model is realistic: individually each invertor decides to herd taking information from the Internet and to follow some strategy that meets certain requirements. Under this assumption, investors may obtain information at once and investment decisions can be taken immediately. It can be said that Internet is a way to explain how individual investors can herd in real financial markets.

The potential of the model to conduct experiments in the financial market is high. The model can be the starting point for studying influence between markets in different countries or between assets in the same market. More modifications are required to the model in order to consider a market with multiple assets that are negotiated with different rules or a market with a different price formation mechanism (e.g. order book).

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