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The impact of disclosure, news and rumors over the formation of security market prices over time

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Much ado about making money: The impact of disclosure, news and rumors over the formation of security market prices over time

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Abstract

This article develops an agent-based model of security market pricing process, capable to capture main stylised facts. It features a collective market pricing mechanism based upon evolving heterogenous expectations that incorporate signals of security issuer fundamental performance over time. Distinctive signaling sources on this performance correspond to institutional mechanisms of information diffusion. These sources differ by duration effect (temporary, persistent, and permanent), confidence, and diffusion degree among investors over space and time. Under full and immediate diffusion and balanced reaction by all the investors, the value of these sources should be consistently and timely integrated by the market price process, implying efficient pricing. By relaxing these quite heroic conditions, we assess the impact of distinctive information sources over market price dynamics, through financial systemic properties such as market price volatility, exuberance and errancy, as well as market liquidity. Our simulation analysis shows that transient information shocks can have permanent effects through mismatching reactions and self-reinforcing feedbacks, involving mispricing in both value and timing relative to the efficient market price series. This mispricing depends on both the information diffusion process and the ongoing information confidence mood among investors over space and time. We illustrate our results through paradigmatic cases of stochastic news, before generalising them to autocorrelated news. Our results are further corroborated by robustness checks over the parameter space.

Keywords: market efficiency, disclosure, information diffusion, agent-based modelling,

JEL Codes: G14, G17, C63, D47, D82, E17, E37, M41, M48

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1 Introduction and Literature Review

Financial students and regulators currently share the notion that an informationally efficient financial market does fully, correctly and timely integrate any new (i.e. unexpected) information that affects the fundamental value of traded security into its price. Informational efficiency implies then that current market price p_t is a well-shaped statistics of the fundamental value F_t, as inferred by information available at that moment in time t (Samuelson 1965, 1973). As (Fama, 1995, p. 4) argues, 'in an efficient market at any point in time the actual price of a security will be a good estimate of its intrinsic value. [...] Although uncertainty concerning intrinsic values will remain, actual prices of securities will wander randomly about their intrinsic values'. Formally:

$$p_t = E(F_t|I_t)$$
$$I_t = \epsilon_t \text{ with } \epsilon_t \text{ i.i.d. } \rightarrow p_t \sim N(F_{mean}, \epsilon_{var})$$

This understanding of market pricing bases upon an equilibrium approach that explains the eventual results of the trading process without going into the details of underlying socioeconomic phenomena. In fact, two distinctive processes appear relevant here:

1. information discovery and interpretation across investors over time (information diffusion);

2. the market trading design that receives, matches and satisfies eventual orders passed by those investors (market microstructure).

From this perspective, equilibrium approaches adopt a reductionist modelling strategy that assumes the correct and timely alignment between market price and fundamental value over time (Cutler et al. 1989; Fama 1991, 1998; McQueen and Roley 1993; Fair 2002), neglecting specific conditions of information diffusion and market microstructure.

From a theoretical perspective, Grossman and Stiglitz (1980) show the impossibility of a perfect informationally efficient market, since informed investors would not have incentive to trade, preventing their privileged information to be translated into market prices. A large body of literature explores this finding investigating whether and which configurations for information diffusion and market microstructure do trigger informational efficiency or inefficiency. In particular, some scholars develop event studies showing statistically significant abnormal returns over public information release time windows (Kothari and Warner 2007a; Antweiler and Frank 2006; Gurun and Butler 2012), and econometric tests showing significant deviations from a well-shaped alignment (LeRoy 2008; Lo and MacKinlay 1988). Accounting and finance scholars investigate the connection between media releases, market sentiment and information dissemination (Tetlock 2007, 2010; Bushee et al. 2010; Huddart et al. 2007; Kothari et al. 2009; Zhang 2006). Behavioural finance challenges the cognitive and behavioural assumptions of the received approach (Subrahmanyam 2008). Financial economics focalises on privileged information and insider trading (Kyle 1985; Jarrow 1992; Benabou and Laroque 1992; Allen and Gale 1992; Allen and Gorton 1992; Damodaran and Liu 1993); as well as market influence and market manipulation (Aggarwal and Wu 2006; Goldstein and Guembel 2008; Misra et al. 2011). Econophysics explores how the coordinating impact of media releases and shocks shapes investors' behaviour and the formation of security prices over time (Harras and Sornette 2011; Zhang 2013; Sornette and Helmstetter 2003). In a nutshell, fully efficient market hypothesis assumes the perfect alignement between the market price series and the fundamental signal series, making the latter virtually irrelevant for investment decision-making. However, existing literature shows that the informational structure does matter for investment choice and has an impact over the overall market pricing process over time.

Drawing upon this literature on the impact of information diffusion and market microstructure over market price formation, our article develops an agent-based model of financial market pricing process, extending the analytical model by Biondi et al. (2012), which is computationally explored by Biondi and Righi (2015). This model reproduces main stylised facts of security market pricing process by featuring: evolving heterogeneous expectations, collective market price mechanism, and distinctive information sources on fundamental performance of the traded security. Our modelling strategy does accept that investors idiosyncratically receive and interpret distinct evolving signals of fundamental performance that jointly deliver noisy information about the security issuer. Heterogeneous investors do form focal price opinions on noisy information, and pass orders through a trading facility that rules over and transforms their orders into ongoing market prices over time. From this institutional economic perspective, informational efficiency of market price formation crucially depends on market microstructure and degree of information diffusion.

In particular, signalling sources correspond to institutional mechanisms of information diffusion. These sources may differ by duration effect (temporary, persistent, and permanent), confidence, and diffusion degree across investors over time. From an heuristic perspective, widely disseminated and trustworthy news point to compulsory or voluntary disclosure by the security issuer; rather widespread and credible news point to financial analysts' and specialised media' opinions; confidential and unreliable news point to rumors and gossips featuring potential and actual investors' communities and social networks. Insider information and trading is a special case of privileged information that remains outside public domain at its early dissemination at least.

In principle, under full and immediate diffusion and a balanced reaction by all the investors, the value content of these sources is expected to be consistently and timely integrated by the market pricing process, implying informationally efficient pricing. Our modelling strategy comprises this situation as a corner solution. By releasing its quite heroic conditions, our model assesses then the impact of distinctive information sources over market price formation, absolute and relative returns, and financial systemic properties such as market price volatility, exuberance and errancy (Biondi and Righi 2015). The latter two properties point to the relative efficiency of the market pricing by denoting the relative distance between the actual market price and its theoretical level (exogenously) inferred by fundamental performance over time. In particular, 'market exuberance' implies a relevant disconnection that persists over a limited time period, while 'market errancy' implies a relevant disconnection that involves permanent effects over market pricing quality.

Our simulation analysis shows that transient information shocks can have persistent (exuberance) and permanent (errancy) effects through mismatching reactions and self-reinforcing feedbacks, involving mispricing in both value content and timing relative to the informationally efficient market price series. Generally speaking, this mispricing depends on both the information diffusion process and the ongoing information confidence mood among investors over space and time. We illustrate our results through paradigmatic cases of stochastic informational news, before generalising them to autocorrelated informational news. Our results are further corroborated by robustness checks over the parameter space. These simulation results are relevant to socio-economic understanding of market pricing process and its regulatory design (Carlton and Fischel 1983; Misra et al. 2011).

2 Model and Notation

Biondi et al. (2012) develop a heterogeneous agents analytical model that generalises received equilibrium approaches to financial market pricing process. This article develops an agent-based version of that model, extended to include two distinctive sources of information about the traded security issuer.

According to (Aoki and Yoshikawa, 2011, chapter 9), two broad categories of chartism and fundamentalism account for most of possible investment strategies. Following Hirota and Sunder (2007) and Heemeijer et al. (2009), we consider a large population of heterogeneous trading investors which form their focal price expectations (upon which they base their trading strategies) according to the following generic function:

$$E_{i,j,t}(p_{t+1}) = p_t + \alpha_{j,t}(p_t - p_{t-1}) - \beta_{i,j,t}\delta_{i,j,t} + \gamma_{i,j,t}\phi_i F_t + I_{i,t}\Delta_{i,t}N_t \tag{1}$$

$$\forall i \in [0,1], \forall j \subset (D;S), \forall t, \text{ with } I_{i,t} = \{0;1\} \text{ and } \Delta \in [0,1]$$

where

$$\delta_{i,j,t} \equiv E_{i,j,t-1}(p_t) - p_t \tag{2}$$

Equation 1 comprises five elements. The first is the past market clearing price p_t. The second is the signal generated by the market about the aggregate price trend $(p_t - p_{t-1})$; the importance given to this market signal is weighted by the market confidence $\alpha_{i,t}$. The third element is the individual forecast revision $\delta_{i,j,t}$; it consists of the difference between investor's past price expectation $E_{i,j,t-1}(p_t)$ and the last clearing market price that was actually realized (Equation 2), weighted by $\beta_{i,t}$, which captures both group and individual heterogeneities. The last two elements denote the formation of an individual opinion based upon distinctive signals of fundamental performance, F_t and N_t, which can be available to individual investors. This opinion is respectively weighted by distinctive individual parameters, $\phi_i\gamma_{i,t}$ and $\Delta_{i,t}$, which capture both group and individual heterogeneities. Concerning the signal N_t, each generic investor i can belong to one of two groups $I_{i,t} = \{0;1\}$ at time t. Group $I_t = 0$ is formed by those investors that do not know (or care about) the news (uninformed investors), while group $I_t = 1$ is formed by investors which do know and care about the news at time t (informed investors). Their belonging can evolve over time according to their evolving attitude and the information dissemination pattern.

According to this framework of analysis, each investor idiosyncratically forms his opinion on the fundamental value of the traded security through two distinctive sources of information: a signalling source F_t that is common knowledge among all the investors, and another signalling source N_t that becomes available only to informed investors (with $I_{i,t} = 1$) at a certain moment in time t. Both sources of information may then drive the market pricing process by framing and shaping the dynamics of investors' opinion and trade over time. In particular, uninformed investors have two distinctive ways to indirectly receive and guess about news N_t information over time: one through market price trend; another one through individual forecast revision $\delta_{i,j,t}$. Along with information diffusion pattern (subsumed by news N_t timing, investors' confidence $\delta_{i,t}$, and dissemination degree $I_{i,t}$), these indirect ways are crucial to the ongoing alignment between the market price series and the informationally efficient price series, determining the relative informational quality of market price process over time.

The last building block of our model is the mechanism through which the market price is formed at every trade time t. Investors' bidding strategy is based on their focal price expectations. Investors can buy, sell or wait for the next period. Before each trade session, each investor wishes to sell one security $S_{i,t}$ if its past clearing market price is lower than his focal price expectation, that is, $p_{t-1} \leq E_{i,t}(p_t)$, while he wishes to buy one security $S_{i,t}$ (committing its available liquidity $L_{i,t-1}$) if the past clearing market price is higher than his focal price expectations, that is, $p_{t-1} > E_{i,t}(p_t)$. The market mechanism collects all the investors' orders and checks whether they can be satisfied at the past clearing price according to each investor's portfolio constraints. Covered orders are then split between the two sides of the market as follows:

$$S \in_i \{E_{i,t-1}(p_t) \leq p_{t-1} \wedge S_{i,t-1} > 0\} \tag{3}$$

$$D \in_i \{E_{i,t-1}(p_t) \geq p_{t-1} \wedge L_{i,t-1} > p_{t-1}\} \tag{4}$$

Based upon covered orders, the market mechanism fixes then the market clearing price according to the following formula (reproducing Biondi et al. 2012):

$$p_{t+1} = \begin{cases} p^{NC} = median(E_{i,t}(p_t)) & \text{if } \overline{P}_{S,t} \leq \underline{P}_{D,t} \\ \\ p^{C} = \frac{\overline{P}_{S,t}(\overline{P}_{D,t} - \underline{P}_{D,t}) + \underline{P}_{D,t}(\overline{P}_{S,t} - \underline{P}_{S,t})}{(\overline{P}_{S,t} - \underline{P}_{S,t}) + (\overline{P}_{D,t} - \underline{P}_{D,t})} & \text{if } \overline{P}_{S,t} \geq \underline{P}_{D,t} \end{cases} \tag{5}$$

With:

$$
\begin{aligned}
\overline{P}_{S,t} &= max[E_{i=0,S,t}(p_{t+1}); E_{i=1,S,t}(p_{t+1})] \\
\underline{P}_{S,t} &= min[E_{i=0,S,t}(p_{t+1}); E_{i=1,S,t}(p_{t+1})] \\
\overline{P}_{D,t} &= max[E_{i=0,D,t}(p_{t+1}); E_{i=1,D,t}(p_{t+1})] \\
\underline{P}_{D,t} &= min[E_{i=0,D,t}(p_{t+1}); E_{i=1,D,t}(p_{t+1})]
\end{aligned}
\tag{6}
$$

At every trading time t, the model assumes an aggregate matching process (in line with Di Guilmi et al. 2012; Foley 1994; Anufriev and Panchenko 2009; Chiarella et al. 2002; Horst 2005). The market mechanism fixes a market clearing price that is central to the price ranking across both sides of the market, satisfying single-security orders $\{S_{i,t}; E_{i,t}(p_t)\}$ through progressive matching between higher ask and lower bid orders, whenever each order is sustainable according to investor's portfolio constraints at the announced clearing price p_t. When matching is feasible, the market mechanism denoted by Equation 6 computes the market clearing price under the assumption of uniform distribution of orders on both sides of the market, based upon the four extreme values expressed by bidding and asking investors on both market sides. When the aggregate price fixing cannot deliver a market clearing price, the market mechanism cancels all the orders and calls a market price p_t from the median of all the expressed prices $E_{i,t}(p_t)$ for that trading session. Aggregate market price dynamics enriches the passage between the individual and the collective level, making the latter irreducible to the former. Each price pattern becomes unique over time and space. Replication of several patterns through simulation enables then to infer regularities on the working of this financial system under its distinctive conditions.

Investors' portfolios comprise shares $S_{i,t}$ and cash $L_{i,t}$, that are updated after each trading session by satisfied orders. In fact, portfolio composition and net worth do not inform investors' expectations over time, since investors form their focal prices on past and next period expectations, posting orders deterministically by comparing their focal prices with past called price (Biondi et al. 2012; Biondi and Righi 2015).

3 Simulation Calibration

Our simulation analysis shall assess the relative impact over market pricing process by distinctive patterns of informational shock N_t. For sake of simulation purpose, we calibrate then the two distinctive signalling sources as follows:

$$F_t = \epsilon_1, \tag{7}$$

$$N_t = N_{shock} + (1-a)\epsilon_2 + aN_{t-1}; \tag{8}$$

with $N_{shock} : N_{shock} \gg F_t$ when it exists, and where a is the autocorrelation coefficient, while ϵ_1 and ϵ_2 are random values extracted from a normal distribution with mean 0 and standard deviation 0.1. This design denotes some basic stylized facts featuring information diffusion: N_{shock} captures a single announcement whose effect may persist over time, while the autocorrelation parameter a captures the reverberation effect that may characterizes the information diffusion process through social media and networks. According to our design, the two information sources F_t and N_t remain independent and are possibly discovered and interpreted by each investor through his own peculiar pattern over time (subsumed by his evolving parameters set). According to our framework of analysis, we can derive a central reference signal of fundamental performance jointly delivered by both signalling sources over time, as follows:

$$FN_t = \sum_t (F_t + N_t) \ \forall t \quad \text{or equivalently} \quad FN_t = FF_t + NN_t \ \forall t \tag{9}$$

Where:

$$FF_t = \sum_t (F_t) \tag{10}$$

$$NN_t = \sum_t (N_t) \tag{11}$$

The intrinsically chaotic dynamics prevents the actual market pricing process to provide a perfect alignment at each moment of time. However, given our calibration, a relatively efficient market pricing is expected to deliver a clearing market price that moves along with this central reference over time. This generalizes received approaches.

This calibration aims at studying the relative impact of distinctive news N_t patterns over market pricing generated by heterogeneous investors' expectations and related trading. Accordingly, am informational shock N_t contains some value content that is perceived by informed investors (with $I_{i,t} = 1$) with a confidence degree $\Delta_{i,t}$ on this value content at time t. Informational shock N_t potential impact can change over time: it will be different from zero as long as its value content is somewhat considered trustworthy, while it goes to zero once its credible value content does disappear. Therefore, a permanent shock N_t is equivalent to an additional information that complements and integrates the fundamental information pattern F_t, while a transient shock N_t is equivalent to a rumor that comes to disturb the fundamental information pattern F_t for a certain time periods sequence.

Investors' expectations parameters from Equation 1 require calibration to perform simulation analysis. This calibration does not purport here to obtain realistic assumptions for them, but to improve comparability between various parameter sets and distinctive signalling sources patterns over the overall parameter space. This space comprises market pricing confidence $\alpha_{i,t}$, settled between 0 et 1 (0.5 being the baseline); signalling source N_t confidence $\Delta_{i,t}$ between 0 and 1 (0.5 being the baseline); and forecasting error weight $\beta_{i,t}$ between 0 and 1 (0.5 being the baseline). In particular, we maintain that confidence in the signalling source F_t is uniform (ϕ_i remaining constant and uniformly distributed between 0 et 1 over time) and centered to 0.5 (with $\gamma_{i,t} = 1 \ \forall i, t$). All these calibrations purport to obtain a symmetric setup around the median investor identified by $\phi_i = 0.5$. This symmetry is reinforced from the fact that all stochastic elements, including F_t, are small and symmetrically or normally distributed. This calibration strategy further connects all relevant market price movements with the signalling source N_t whose impact is under investigation.

According to our framework of analysis, investors do trade on disagreement: their order can be satisfied only when it matches an opposite order from another investor during the same trading session at time t. This potential illiquidity condition may undermine the actual impact of informational shocks at time t and over time periods. Moreover, single-security orders do not allow volumes to affect trade impact over market pricing, while investors' portfolios are calibrated to prevent them to become budget constrained over time. All these conditions undermine informational shocks impact, reinforcing our simulation results.

We run simulations through a baseline case of stochastic informational news N_t patterns, before generalising it to autocorrelated informational news N_t patterns. We apply the same time window for baseline informational shock patterns, in order to denote ex ante, ongoing and ex post situations related to persistent information release over time: the shock N_t does not appear before 100 periods (time phase A, ex ante), lasts for 100 periods (time phase B, ongoing), and disappears throughout the last 100 periods (time phase C, ex post). Concerning time window for autocorrelated informational news patterns, the shock N_t is activated at period $t = 10$ and disappears at period $t = 290$, while the market price formation lasts between 1 and 300 as in the previous case. This latter case allows studying the reverberation effect that may characterize the information diffusion process, rather than the single jump case that feature the previous case.

Our simulation results are further corroborated by robustness checks over the overall parameter space under various configurations. Among others, we analyse several descriptive statistics over the full range of the share of informed investors $SI \in [0;1]$ and the degree of speculative attitudes $\alpha_{i,t} \in [0,1]$.

In order to focalise on the impact of informational shock patterns N_t on market price formation over time, we provide most results by computing the change in descriptive statistics between the patterns with and without shocks at either each time step or each simulation round. Both patterns are computed under the same parameter space and random seed. Every change in descriptive statistics depends then exclusively on the impact of the informational shock that is activated. For simulation purpose, we fix the initial fundamental information signal $F_{t=0} = 10$ at the same level as the initial security price $p_{t=0} = 10$. We design the informational structure to study two distinctive phenomena: its evolution over time, and its diffusion through the social space of investors.

Concerning its temporal evolution, we study two regimes of informational shock patterns: stochastic and autocorrelated. Under stochastic informational shock patterns, autocorrelation parameter $a = 0$ and the shock level N_{shock} is fixed to 2 during the activation period which lasts between $t = 100$ and $t = 200$. This implies that, at the time period $t = 100$ of its activation, the shock N_t incorporates a positive increase of +20% relative to the reference fundamental information $F_t = 10$. The dynamics of N_t then follows Equation 8 until $t = 200$, when it is reversed by -2 at $t = 200$ and remains zero throughout the last 100 periods. This stochastic informational shock pattern allows studying the effect of one single announcement whose effect may persist over time.

Under auto-correlated informational shock patterns, the informational shock level $N_{shock} = 0$ while the autocorrelation parameter $a = 0.5$. With autocorrelation $(0 < a \leq 1)$, each informational shock N_t has a persistent echo that reverberates for several time periods after its appearance, capturing the ongoing repetition and progressive diffusion of noisy information through social opinion processes over time. This autocorrelated shock is activated from time period $t = 10$ to time period $t = 290$, while market lasts 300 periods as in the previous case. This implies that the mean value content of the informational shock is zero on average over the whole time window.

This autocorrelation calibration allows then studying the dynamic effect of persistent intensity of informational shocks relative to the stochastic case (with $a = 0$) that denotes informational shocks as random walks.

In sum, we study two distinctive cases: one stochastic news flow characterized by a single announcement whose effect persists over time; another autocorrelated news flow that features reverberation effects over time. Concerning information diffusion over the social space of investors, we introduce three paradigmatic scenarios of information diffusion:

- **Disclosure**: widely disseminated news. This scenario points to compulsory or voluntary disclosure by the security issuer by extracting the share of informed investors at each simulation round from a triangular distribution centered around 0.85 with a width of 0.10;

- **Media coverage**: rather widespread and credible news. This scenario points to financial analysts' and specialised media' opinions by extracting the share of informed investors at each simulation round from a triangular distribution centered around 0.5 with a width of 0.10;

- **Rumors**: confidential and unreliable news spread through investors' communities. This scenario points to rumors and gossips featuring potential and actual investors' communities and social networks by extracting the share of informed investors at each simulation round from a triangular distribution centered around 0.15 with a width of 0.10.

4 Simulation Results

This section summarises our simulation results for stochastic informational shock patterns (Section 4.1) and autocorrelated informational shock patterns (Section 4.2). For each shock type, our analysis covers four different matters: market informational efficiency; distribution of prices and returns; market volatility, liquidity and satisfaction; and market exuberance.

Market informational efficiency concerns the capacity of the market pricing process to timely and consistently integrate the flow of new information that is delivered by FN_t over time. To measure this effect, we introduce a specific frame of analysis that is explained in paragraph 4.1 below. Distribution of market prices and return captures the aggregate behaviour of market pricing process over time and circumstances. We denote this behaviour through usual definitions of price difference and price relative returns, computed in or compared between the two distinctive cases without and with news flow:

$$\text{Price difference}_t = p_t - p_{t-1} \tag{12}$$

$$\text{Price return}_t = \frac{p_t - p_{t-1}}{p_{t-1}} \tag{13}$$

Market volatility, liquidity and satisfaction concern one fundamental quality of the market pricing process over time when only the market price series characteristics are under examination.

In particular, we denote market volatility through the following descriptive statistics, computed in or compared between the two distinctive cases without and with news flow:

$$\text{Market volatility} = \frac{Std(p_t)}{Mean(p_t)} \tag{14}$$

In our frame of analysis, market liquidity is better denoted by the relative capacity of the market matching protocol to satisfy demand, computed as follows:

$$\text{Mkt}_{\text{satisfaction}}(t) = \frac{min(\text{size}(D_t), \text{size}(S_t)) \cdot 100}{max(\text{size}(S_t), \text{size}(D_t))} \tag{15}$$

Market exuberance (Shiller 2003) concerns another fundamental quality of the market pricing process over time, when the ongoing alignment between the market price series and the overarching fundamentals is under examination. In particular, we assess permanent disalignment between the two series that are labelled 'market errance' hereafter (Biondi and Righi 2015). We denote this quality through some descriptive statistics, computed in or compared between the two distinctive cases without and with news flow.

We introduce Exuberance ($Exub_t$), which denotes the difference between the price difference ($p_t^{with} - p_t$) and the cumulated news NN_t as follows:

$$Exub_t = p_t^{with} - p_t - NN_t \ \ \forall t \tag{16}$$

In a fully efficient market $Exub_t = 0, \ \ \forall t$.

We further consider the cumulated absolute sum of this variable over the time window as follows:

$$\text{Total Absolute Exuberance} = \sum_t \mid \left[p_t^{with} - p_t - NN_t \right] \mid \tag{17}$$

Market exuberance points to the capacity of the market price series to capture the novel information delivered by the fundamental signal series without adding noise in the process. This added noise can be denoted - at each time step - by the following descriptive statistics:

$$\text{AddedNoise}_t = \left| \frac{p_t^{with}}{FF_t + NN_t} - \frac{p_t}{FF_t} \right| \tag{18}$$

This measure captures the relative noise added by the presence of the news over the noise that already existed without it, since our market pricing process is endogenously noisy. We further consider its cumulated absolute sum over the time window:

$$\text{Total Added Noise} = \sum_t |\text{AddedNoise}_t| \tag{19}$$

We also introduce the following descriptive statistics

$$\text{Distance} = \frac{p_t^{with} - FN_{t-1}}{FN_{t-1}} \tag{20}$$

which denotes the relative distance between the current period market price and the past period fundamental signal of reference for that same price, that is, the fundamental signal that was common knowledge and then potentially exploitable by investors to form their idiosyncratic expectations.

4.1 Analysis of stochastic news flow

According to our frame of analysis, stochastic information shock N_t has a distinctive time evolution over three time phases of reference. In particular:

- Time phase A denotes the initial time window when informational shock is not active (all investors are then equally informed). For simulation purpose, it is fixed between $t = 1$ and $t = 99$;

- Time phase B denotes the intermediate time window when informational shock is active and known only by informed investors, being fixed between $t = 100$ and $t = 199$;

- Time phase C denotes the final time window when informational shock disappears, between $t = 200$ and $t = 300$.

This setting enables analysing our model from an evolutionary perspective throughout the three time windows.

Market informational efficiency points to the capacity of market pricing process to align the market price series with its fundamental benchmark denoted by FN_t over time. Three distinctive behaviours of the financial system can be disentangled according to three mutually exclusive scenarios. In the 'satisfying' scenario, the market price series remains comfortably near to the fundamental benchmark series over time. In the 'errant' scenario (Biondi and Righi 2015), the market price series shows permanent departure from the fundamental benchmark series over time. In the 'exuberant' scenario (Shiller 2002), the market price series shows material but transient departure from the fundamental benchmark series over time. Our simulation calibration for stochastic informational shocks allows disentangling these three scenarios by focusing on a descriptive statistics labelled Exuberance ($Exub_t$), defined by Equation 16.

For simulation purpose, we define a benchmark level of divergence $\bar{\epsilon}$ based upon the maximum values of F_t and N_t (excluding its jumps dependent on the $N_{level} = 2$) as follows:

$$\bar{\epsilon} = 2 \cdot |\max(F) + \max(N_{N \neq N_{shock}})| \tag{21}$$

When the stochastic informational shock pattern N_t disappears after period $t = 200$, the market price series should progressively realign with the fundamental signal series F_t throughout the last time window C. Accordingly, we define a market price series as 'errant' when its average value of $Exub_t$ over the 10% of the final time period window C remains larger than the benchmark level epsilon, in other terms if $\overline{(|Exub_{290 \leq t \leq 300})|} > \bar{\epsilon}$.

If a market series is not errant, it is considered 'exuberant' when, during the time phases windows B and C that follow the activation of the informational shock (that is, when $t \in [100; 300]$), its $Exub_t$ exceeds $\bar{\epsilon}$ for more than 10% of time periods.

A market price series is considered 'satisfying' when it is neither 'errant' nor 'exuberant', implying that it remains near to the benchmark level of FN_t for most of the time periods. On this basis, we run 100 simulations and count how much cases occur under the three scenarios. Figure 1 summarises simulation results. In a majority of cases, the market price series cannot consistently align with the benchmark level of reference, showing 'errant' or 'exuberant' behaviour. This result is worsened by information diffusion, since market price series quality decreases when the share of informed investors IS increases. Only at the theoretical level when all the investors are fully informed (i.e., when $IS = 1$), the majority of market price series becomes 'satisfying'.

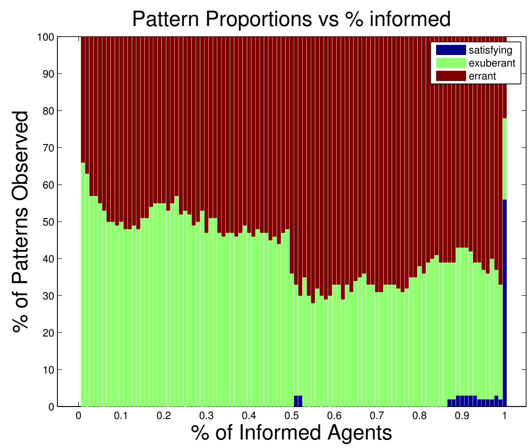

Figure 1: For each given share of informed we run 100 simulations counting how many of them turn out to be of type 'satyfactory', 'errant', and 'exuberant'. We plot the proportions with respect to the share of informed investors. The three types are mutually exclusive. Definitions are provided in the main text in Section 4.1

This result makes full efficient market efficiency to become a limited interest corner case. When investors are heterogeneous and trade on disagreement through an aggregate matching mechanism, the market price fixing does timely and consistently incorporate the fundamental signal series only in a very limited subset of circumstances. Market exuberance and errancy are then the norm rather than the exception, according to our simulation analysis.

Prices and Returns The rest of this section analyses the evolutionary pattern of several descriptive statistics under the three paradigmatic scenarios of information diffusion (disclosure, media coverage and rumors) introduced above. At the same time, we further test their sensitivity to the weight $\alpha_{i,t}$ that each investor attributes to the market price trend when forming his expectations (Equation 1). This parameter captures the overall market confidence that results from social opinion dynamics among investors (Biondi et al. 2012; Biondi and Righi 2015). In particular, when $\alpha_{i,t} \to 0$ and $\alpha_{i,t} < 0.5$, investors tend to disregard the market signal, denoting fundamentalist (conservative) attitudes. Vice-versa, when $\alpha_{i,t} \to 1$ and $\alpha_{i,t} > 0.5$, investor tend to overvalue the market signal, denoting speculative attitudes.

We plot the temporal structure of the price difference between cases with and without informational shock (Figure 3), his CDF (Figure 4), the temporal structure of returns (Equation 13) with informational shock (Figure 2), and the CDF of the difference in relative returns between cases with and without shock (5).

Speculative attitudes consistently increase the dispersion of prices across the CDFs under

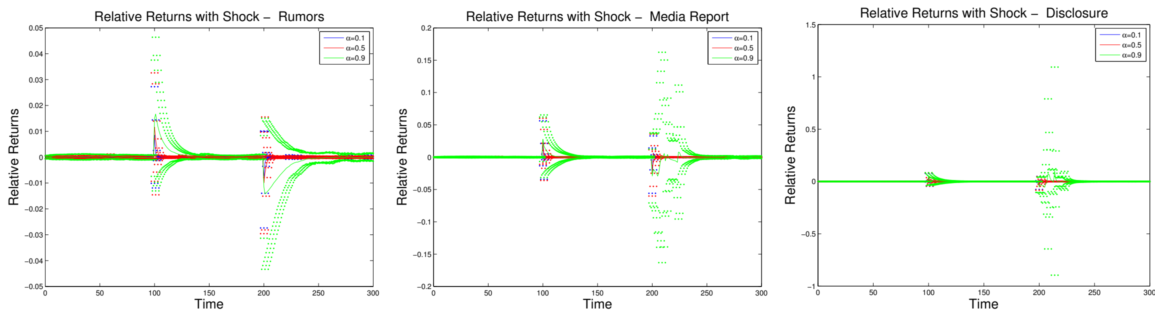

Figure 2: Temporal structure of relative returns (case with shock). Returns are defined in Equation 13 Mean and Standard Deviation from 100 simulations of 300 periods are reported for each time period.

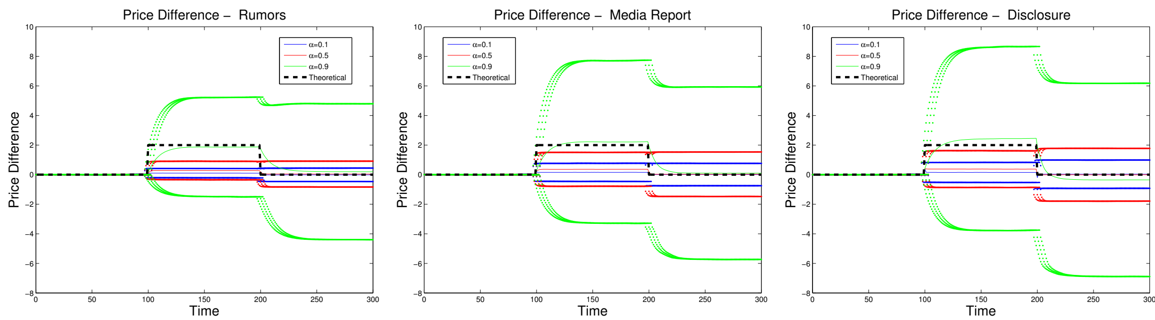

Figure 3: Temporal structure of price difference between cases with and without shock: $p_t^{with} - p_t$ $\forall t$. Mean and Standard Deviation from 100 simulations of 300 periods are reported for each time period.

all the information diffusion scenarios. In fact, relative returns show a distinctive behaviour across the various scenarios. While speculative attitudes tend to increase the dispersion of returns across the CDFs, the increased share of informed investors IS strongly and consistently reduces this dispersion, making windfall returns more rare and small under the disclosure regime. In particular, our simulation results show that price difference range (Figure 3) is clearly increased after the activation of informational shock and that, during the time phase C, it never comes back to the levels of time phase A, when this shock was not yet active. Speculative (conservative) attitudes tend to further widen this range, while conservative attitudes tend to reduce it, under all the information diffusion (Figures 3 and 4) This effect is exacerbated by information diffusion, since more investors do react to flow of news shock.

At the same time, return structure shows a distinctive behaviour over time (Figure 2). In line with price difference, speculative attitudes tend to widen the range of returns. However, information diffusion has a clear-cut effect on returns: rumors involve a larger level impact

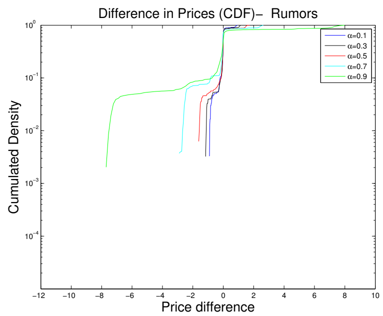

Figure 4: CDF of price difference between cases with and without shock: $p_t^{with} - p_t$. The CDF is computed plotting together data from 100 simulations, each 300 time periods long.

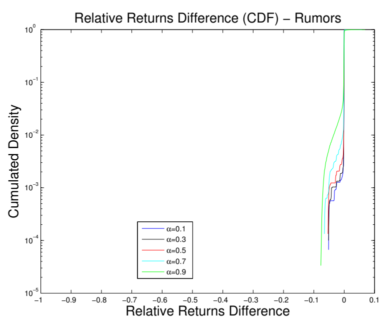

Figure 5: CDF of Difference between cases with and without shock on Relative Returns. Relative Returns (Equation 13) are defined respectively as: $\frac{p_t^{with} - p_{t-1}^{with}}{p_{t-1}^{with}}$ for the case with shock and $\frac{p_t - p_{t-1}}{p_{t-1}}$ for the case without shocks. Distributions are computed for 100 simulations, each providing data for 300 time periods.

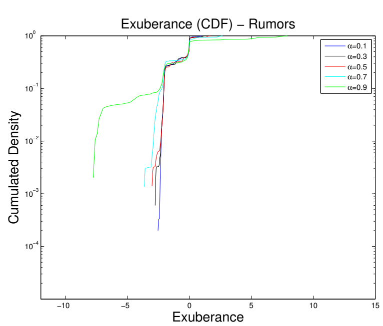

Figure 6: Exuberance defined according to Eq. 12: $p_t^{with} - p_t - NN_t$. Distributions are computed for 100 simulations, each providing data for 300 time periods.

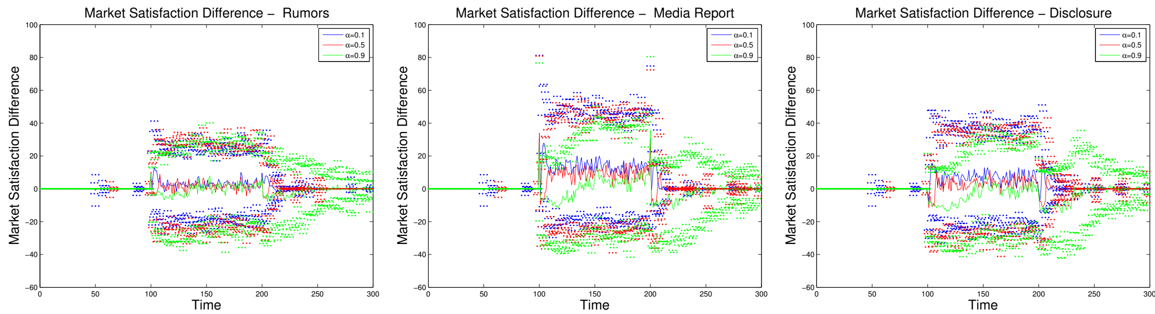

Figure 7: Temporal structure of market satisfaction difference between cases with and without shock. Market satisfaction is computed according to Equation 15. Mean and Standard Deviation from 100 simulations of 300 periods are reported for each time period.

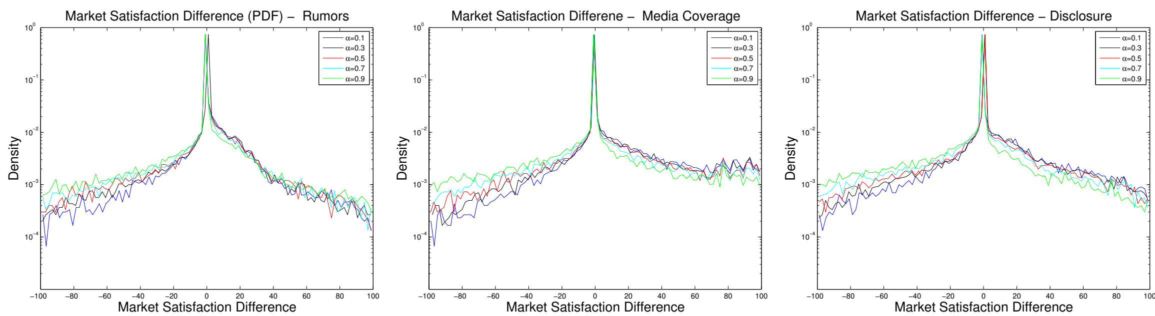

Figure 8: Distribution of Market satisfaction (Eq. 15) difference between case with and without shock. Distributions are computed for 100 simulations, each providing data for 300 time periods.

around the switching time periods of $t = 100$ and $t = 200$, with a longer echo thereafter; media coverage consistently reduces both the level impact and its echo, while the disclosure scenario minimises both effects under all degrees of speculative (or conservative) attitudes. Moreover, speculative attitudes tend to further widen the relative returns width, while conservative attitudes tend to reduce it (Figure 4). This effect is exacerbated by information diffusion, since more investors do react to flow of news shock.

Notice that, for all information diffusion and almost all degrees of speculative attitudes, relative returns are lower when the news is introduced (Figure 5), since news diffusion increases heterogeneity, facilitating market order satisfaction.

Market satisfaction and Volatility The variance of market satisfaction (Figure 7) are increased when the informational shock is active (time phase B). The increased variance - relative to phase A - persists in phase C, although progressively reducing as time passes.

Market satisfaction average value is bigger than zero only during the activation time

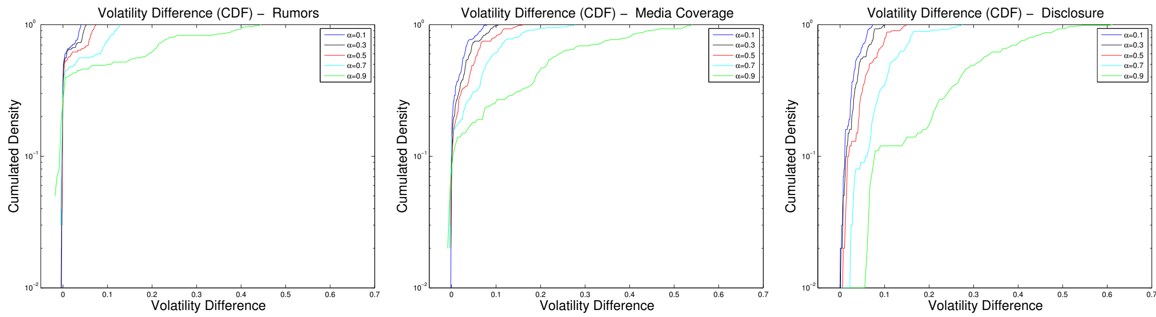

Figure 9: CDF of volatility difference between cases with and without shock. Volatility is defined according to Equation 14. Distributions are computed considering the difference of the volatility expressed in 100 simulations.

window B, showing the positive liquidity effect involved by increased heterogeneity in expectations (implying more divergent trade strategies), since investors trade on disagreement according to our model.

These results suggest that the introduction of an information source, allows has long-lasting effects on the market liquidity increasing its possible variations. This is true even when only a small portion of agents are aware of the news.

Market satisfaction shows a featured response to speculative attitudes as captured by higher values of parameter $\alpha_{i,t}$ (Biondi and Righi 2015). More speculative attitudes tend to endogenously reduce market satisfaction, while conservative attitudes tend to increase it (Figure 8), under all the information diffusion scenarios. This effect is exacerbated by information diffusion, since more investors do react to flow of news shock (Figure 8), as shown by the different distribution shapes under the various news scenarios (rumors, media coverage and disclosure).

Market volatility shows fat tails in its distribution (Figure 9). These tails are exacerbated by speculative attitudes, while are reduced by conservative attitudes in investors behaviour (Figure 9). Under all the information diffusion scenarios, volatility increases along with $\alpha_{i,t}$, especially under speculative attitudes when $\alpha_{i,t} \gg 0.5$. It is also significant that volatility increases consistently with larger information diffusion IS, confirming its dependency on the overarching informational process (Figure 9).

Market informational efficiency Concerning our measure of added noise (Equation 18), under the three scenarios (Figures 10 and 11), conservative attitudes (when $\alpha < 0.5$) tend to decrease relative added noise, while speculative attitudes (when $\alpha_{i,t} > 0.5$) increase it

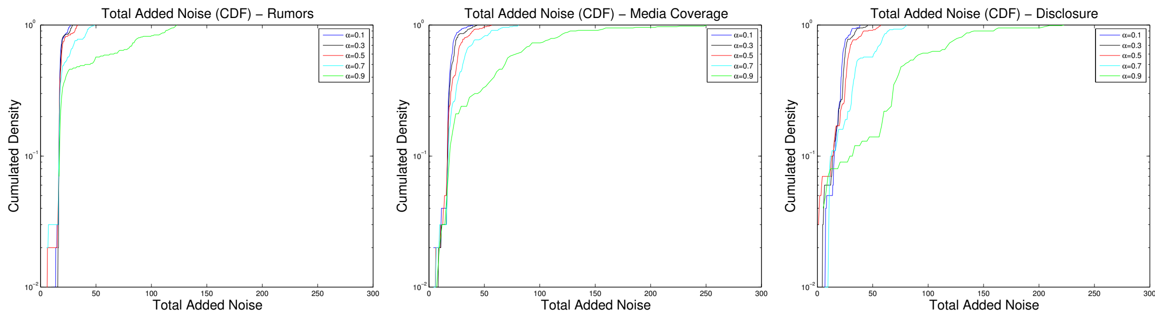

Figure 10: CDF of Total Added Noise (Equation 19). Distributions are computed from values from 100 simulations, using data from time steps > 100.

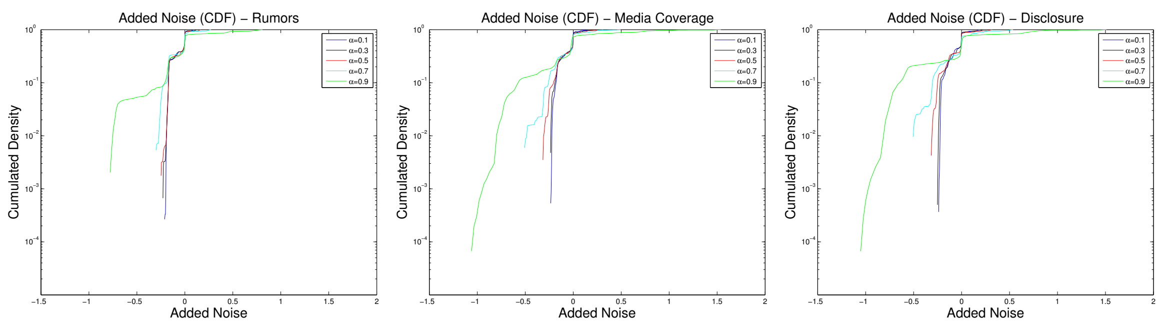

Figure 11: CDF of Added Noise (Equation 18). Distributions are computed from values from 100 simulations, using data from each of their 300 time periods.

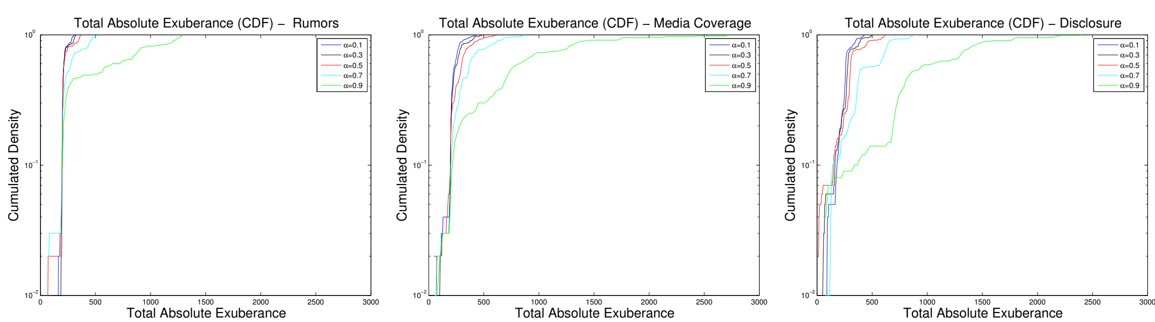

Figure 12: CDF of Total Absolute exuberance (Equation 17). Distributions are computed from values from 100 simulations, using data from each of the 300 time periods.

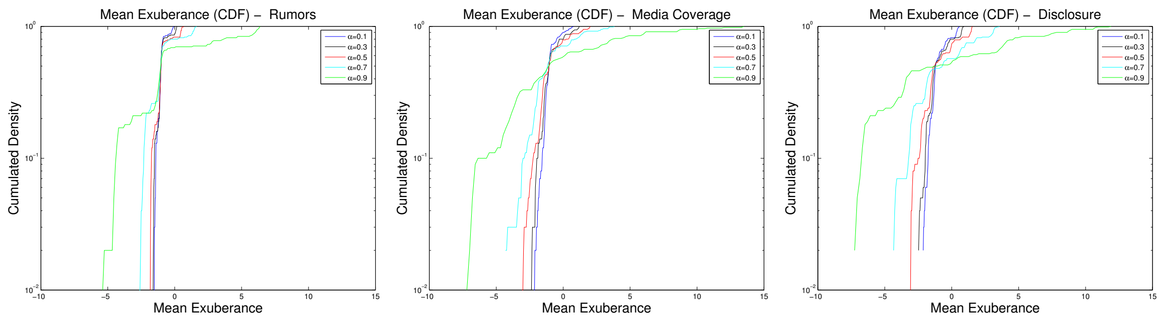

Figure 13: Average Exuberance computed as $\overline{Exub} = mean(Exub_{t\geq 100})$, where $Exub_t = p_t^{with} - p_t - NN_t$.

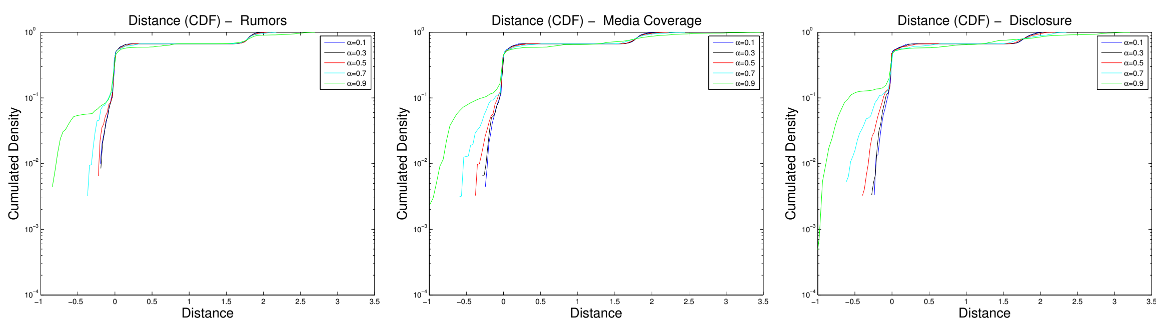

Figure 14: CDF of the Distance (Equation 20). Distributions are computed from values from 100 simulations, using data from each of the 300 time periods.

relative to the balanced attitudes (when $\alpha_{i,t} = 0.5$). However, speculative attitudes clearly enhance relative added noise showing extreme events in the highest amounts of the CDFs under all the information diffusion scenarios.

A similar message is delivered by our coefficient of total absolute exuberance defined in Equation 17 (Figure 12). Again, under all the information diffusion scenarios, this measure is reduced by conservative attitudes (which remain near to the balanced case when $\alpha_{i,t} = 0.5$), while speculative attitudes (when $\alpha_{i,t} \to 1$ and $\alpha_{i,t} > 0.5$) exacerbate total absolute exuberance showing extreme positive events.

Our measure of average exuberance (Figure 6 and 13) completes previous results. Under all the information diffusion scenarios, average exuberance moves from more extreme negative values to more extreme positive values all along with the $\alpha_{i,t}$ progression between 0.1 and 0.9. This clearly shows that previous results depend on the consistent distance that speculative attitudes generate between the fundamental signal series FN_t and the market price series with informational shock. More the market mood is speculative, more the market price diverges from the combined fundamental signal of reference through time.

4.2 Analysis of auto-correlated news flow

Simulation results under stochastic informational shocks can be generalised by introducing autocorrelated informational shock patterns. In particular, this section compares descriptive statistics between the previous case without autocorrelation ($a = 0$), which denotes the news flow as a random walk, and the new case with autocorrelation (with autocorrelation parameter fixed at $a = 0.5$), under the three scenarios of information diffusion: disclosure; media coverage; and rumors. In this case we consider a setup where the news is active from $t = 0$ and $t = 290$ and where there is no large jump in the value of the news but a series of small auto-correlated changes through time. This latter case allows studying the reverberation effect that may characterize the information diffusion through time and space. For simulation purpose, hereafter, the information weight $\Delta_{i,t}$ is fixed at its central level of $\Delta_{i,t} = 0.5$ for all the investors. Moreover, investors are denoted by neutral market mood ($\alpha_{i,t} = 0.5$), meaning that they are neither speculative nor conservative in their collective opinion on the market price trend $p_t - p_{t-1}$.

Market informational efficiency In order to extend and corroborate our simulation results under stochastic news flow, we replicate our measurement protocol for market informational efficiency under autocorrelated news flow. Our measurement protocol points to the exuberance that the market pricing process adds over time and circumstances to the fundamental signals of reference F_t and N_t. Therefore, we can define the following mutually exclusive regimes based upon the variable $Exub_t$ (Equation 16):

- Errant regime: a market price series is 'errant' if the average value of $Exub_t$ in the last 10% of all the periods is at least two times the maximum value of F_t plus the maximum value of N_t (exuberance threshold, hereafter);

- Exuberant regime: a market price series is 'exuberant' if, in at least 10% of all the periods, the $Exub_t$ value exceeds the exuberance threshold;

- Satisficing regime: a market price series is 'satisficing' if it is not either errant or exuberant.

Our simulation results with autocorrelated news flow (Figure 15) corroborate and generalise the results already obtained with stochastic news flow. Only when all the investor have perfect consensus and information ($IS = 1$), the market pricing process delivers a satisficing pricing quality in the majority of circumstances (virtually always, with stochastic news flows). However, when this quite heroic assumption is relaxed, the market pricing process is far less than efficient, showing both exuberant and errant behaviours over time in the large majority of circumstances (Figure 15). For $a = 0$ we observe a tendency of the proportion of exuberant cases to decrease along with the proportion of informed agents, the opposite is true when the auto-correlation is set to $a = 0.5$.

Distribution of Prices and Returns The persistence in the informational shocks introduced by autocorrelation does not seem to have a distinctive impact on distribution of prices and returns. The PDFs show similar shapes for market prices (Figure 16) and returns (Figure 17). Fat tails under the disclosure scenario seem to be reduced by autocorrelation, which tends then to align this scenario with the media coverage. Autocorrelation has a relatively positive effect when information diffusion is large, when investors are widely and uniformly informed and hold neutral speculative expectations neutral ($\alpha_{i,t} = 0.5$).

However, information diffusion appears to have a negative quality impact on both series, reinforcing the presence of extreme events that features market prices divergent from the reference central benchmark of 10. Under the disclosure scenario, larger information diffusion

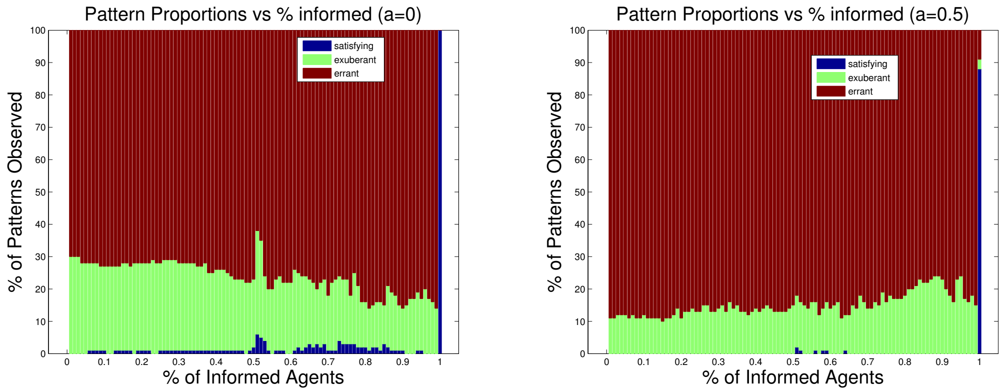

Figure 15: For each given share of informed we run 100 simulations counting how many of them turn out to be of type 'satyfactory', 'errant', and 'exuberant'. We plot the proportions with respect to the share of informed investors. The three types are mutually exclusive. Definitions are provided in the main text in Section 4.1

(with increasing share of informed investors IS) does only appear to reduce extreme negative reactions in both series, without reshaping the overall distribution structure.

Market satisfaction and Volatility Concerning market satisfaction (Figure 18), the information flow confirms its negative impact that depends on information diffusion. When the shock is limitedly known (rumors scenario) or largely widespread and shared (disclosure scenario), investors' heterogeneity is reduced, implying less capacity of the aggregate market matching process to satisfy demand. Therefore, media coverage scenario consistently increases market satisfaction in both stochastic and autocorrelated news flows. This is especially apparent in the right side of the distribution, where market satisfaction is increased relative to the baseline case without news. In particular, the media coverage scenario is the most akin to generate arbitrage opportunities by adding heterogeneity and then liquidity to the market trading.

Concerning market volatility (Figure 19), the news tends to increase volatility under all kind of news flows. This impact is exacerbated by information diffusion, as for more investors know and react on the flows, reshaping indeed the market pricing process by incorporating the ongoing news flow in their orders.

Market informational efficiency The capacity of market pricing process to align with the ongoing reference benchmark denoted by FN_t (Equation 9) over time relates to market exuberance and errancy. This phenomenon is captured here by descriptive statistics of exu-

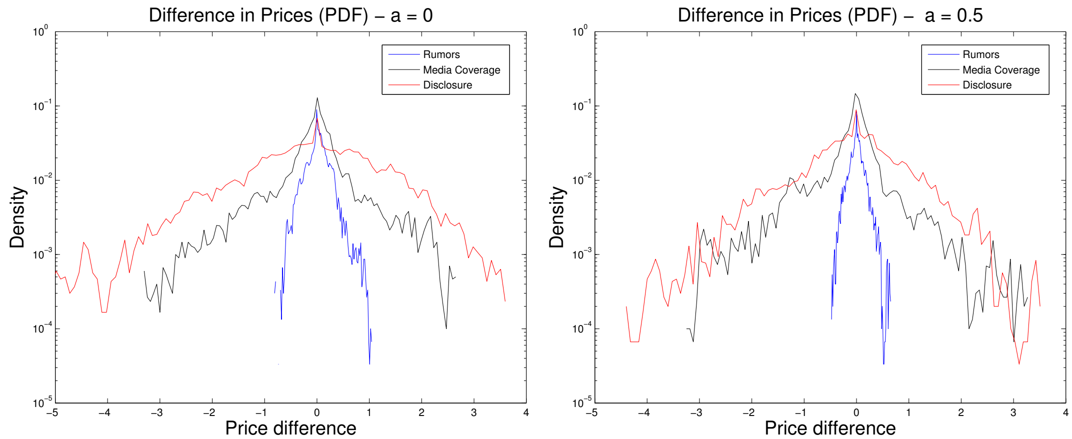

Figure 16: PDF of the Difference in prices $p_t^{with} - p_t$ (between with and without shock, on each single data) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$.

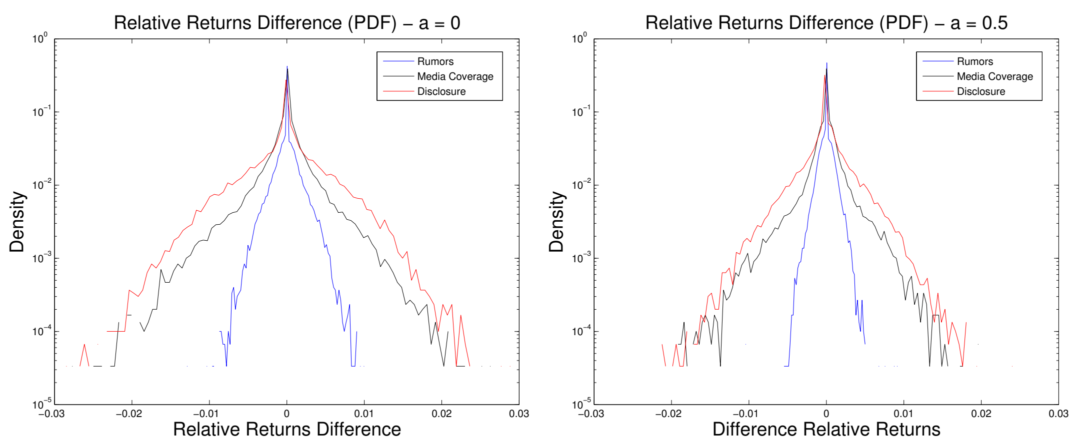

Figure 17: PDF of Difference in Relative Returns (between with and without shock, on each single data) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Relative returns are compute respectively as: $Returns_t^{with} = \frac{p_t^{with} - p_{t-1}^{with}}{p_{t-1}^{with}}$ for the case with shock and $Returns_t = \frac{p_t - p_{t-1}}{p_{t-1}}$ for the case without shock. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$

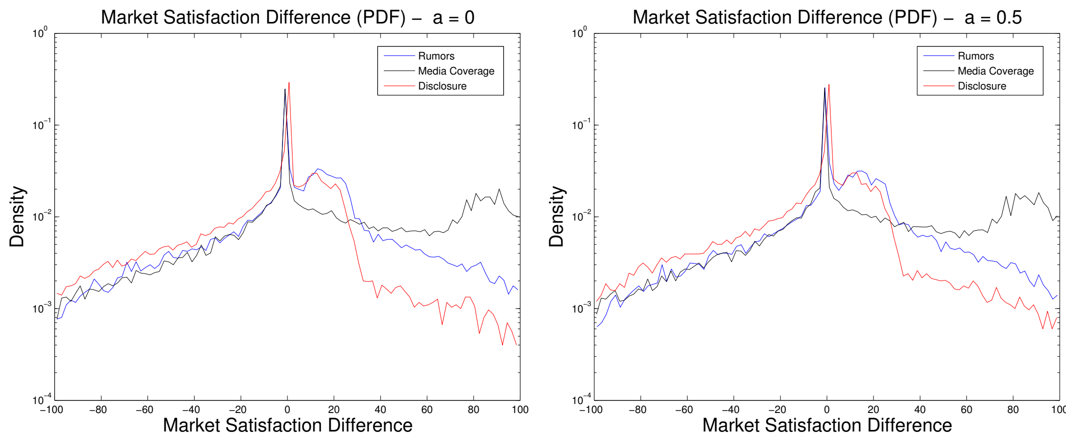

Figure 18: PDF of Difference Market Satisfaction (between the cases with and without shock), as defined in Equation 15. Distributions are computed from 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$

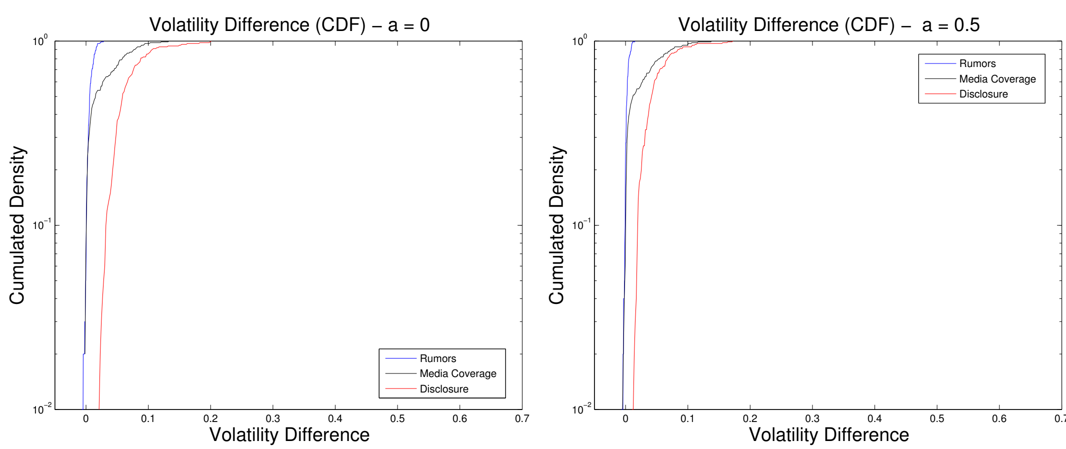

Figure 19: CDF of Market Volatility between the cases with and without shock defined respectively as $\frac{Std(p_t^{with})}{mean(p_t^{with})}$ and $\frac{Std(p_t)}{mean(p_t)}$. Distributions are computed from 100 simulations (for each combination of auto-correlation of shocks and degree of information). One value for each simulation. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$.

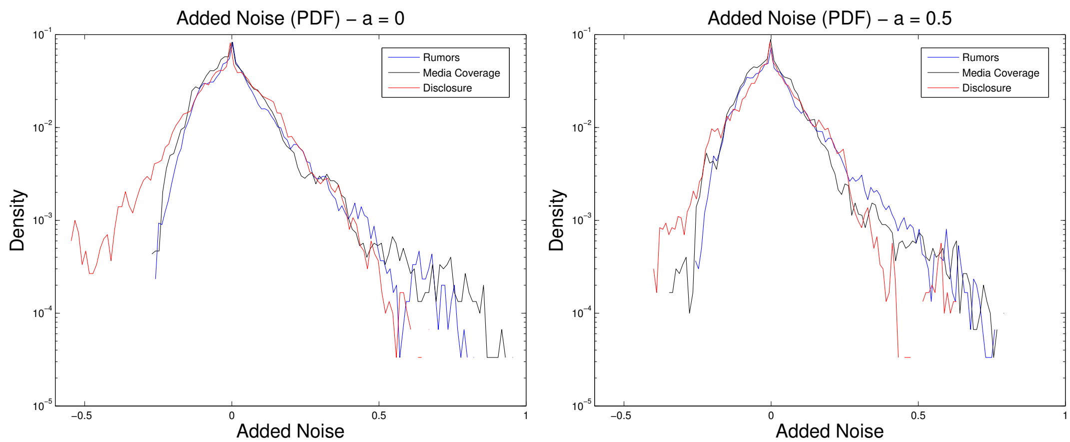

Figure 20: Added noise (Eq. 18) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$

berance (Equations 16), added noise (Equations 18) and distance (Equation 20). Concerning relative added noise (Figure 20 and Figure 21), persistence of information shocks does not reshape the main distribution structure. It seems only to reduce extreme negative events under the disclosure scenario.

A similar result holds for total absolute exuberance (Figure 22). While exuberance should remain near to zero in a relatively efficient market pricing process, all the scenarios show material departure from this benchmark, both with and without persistent intensity of informational shocks (autocorrelation). Concerning the disclosure scenario, pricing quality seems to be improved under the autocorrelated regime, aligning it with the other information diffusion regimes. This seems to corroborate the positive effect of reverberation when investors are widely and uniformly informed and hold neutral speculative expectations neutral ($\alpha_{i,t} = 0.5$).

Concerning distance (Figure 23), this measure should remain near zero in a relatively efficient market pricing process. However, our simulation results confirm a material and consistent departure from zero under all information diffusion scenarios, under both stochastic and autocorrelated shock flows.

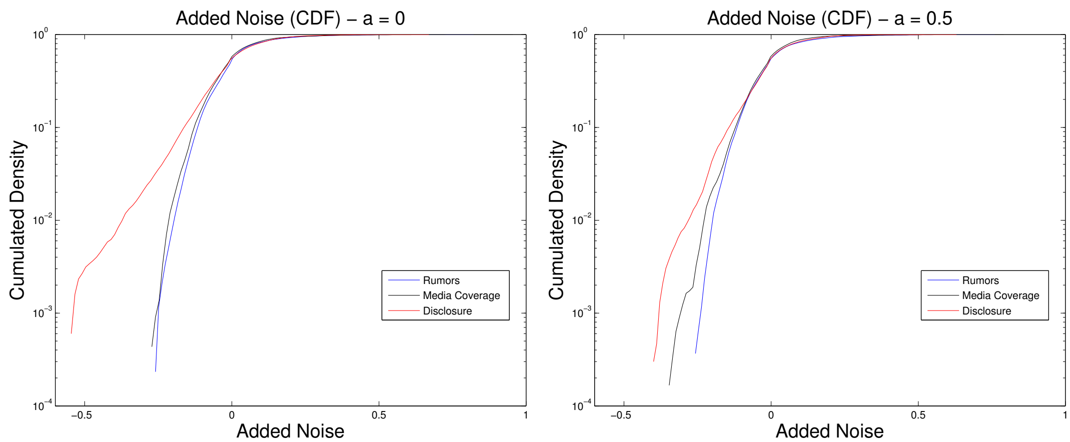

Figure 21: CDF of Added Noise (Eq. 18) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$

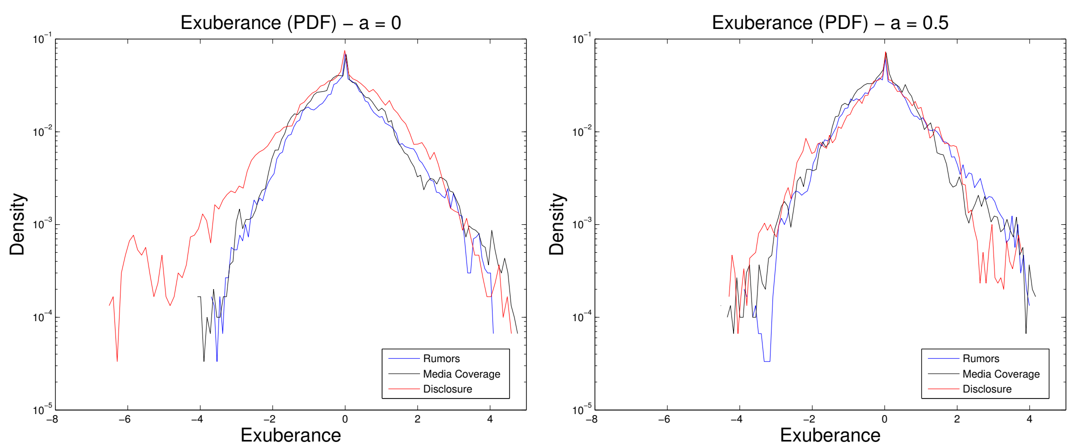

Figure 22: PDF of Exuberance in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Each Figure is a different level of autocorrelation. Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$. Exuberance is computed as: $Exub_t = p_{with} + P - NN_t$ according to Equation 12

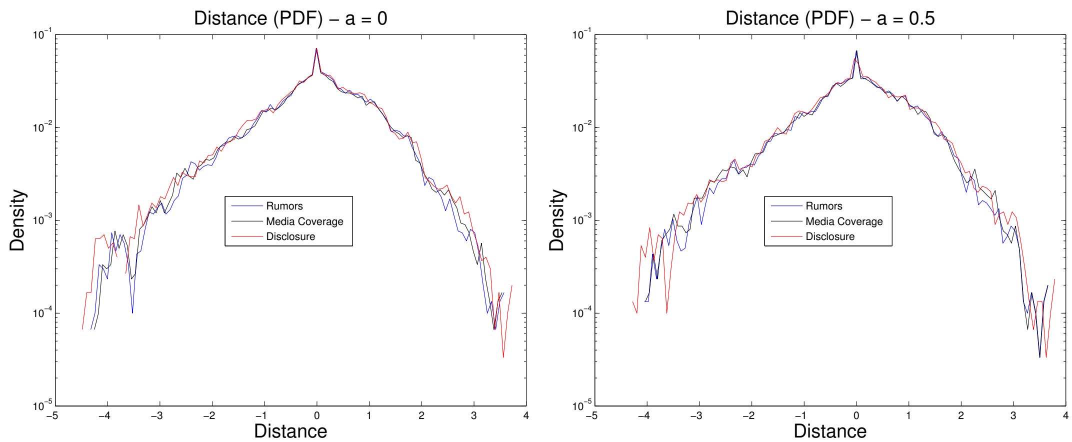

Figure 23: PDF of Distance in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Each Figure is a different level of autocorrelation. Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$. Distance is computed as: $Distance = \frac{p_t^{with} - FN_{t-1}}{FN_{t-1}}$.

5 Conclusive remarks

Our simulation analysis shows that transient information shocks can have permanent effects through mismatching reactions and self-reinforcing feedbacks, involving mispricing in both value and timing relative to the efficient market price series. Generally speaking, this mis-pricing depends on both the information diffusion process and the ongoing information confidence mood among investors over space and time. Our results were illustrated through paradigmatic cases of stochastic and autocorrelated informational shocks under distinctive scenarios of information diffusion (disclosure; media coverage; rumors). These results were further corroborated by sensitivity analysis over the parameter space, showing the distinctive impact of speculative (conservative) attitudes by individual investors on the overall performance of the financial system.

In conclusion, only when all the investors are fully informed, and their market confidence is neutral, the market clearing pricing delivers a relatively efficient market price over time. By relaxing these quite heroic assumptions, the market pricing process shows material and persistent divergence from the fundamental signal of reference through time, while market volatility is increased by the presence of news. Moreover, technical efficiency denoted by relative returns shows an aggregate behavior that differs from fundamental efficiency related to alignment with the fundamental signal flow: although disclosure appears to reduce size and persistency of abnormal returns, it does not imply a better alignment of the market price series with the fundamental signal series through time.

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Much ado about making money: The impact of disclosure, news and rumours over the formation of security market prices over time
Supplementary Material

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1 Additional Figures for the Stochastic case

We hereby report additional figures concerning the Added Noise and the Distance measures in the case of stochastic news flows.

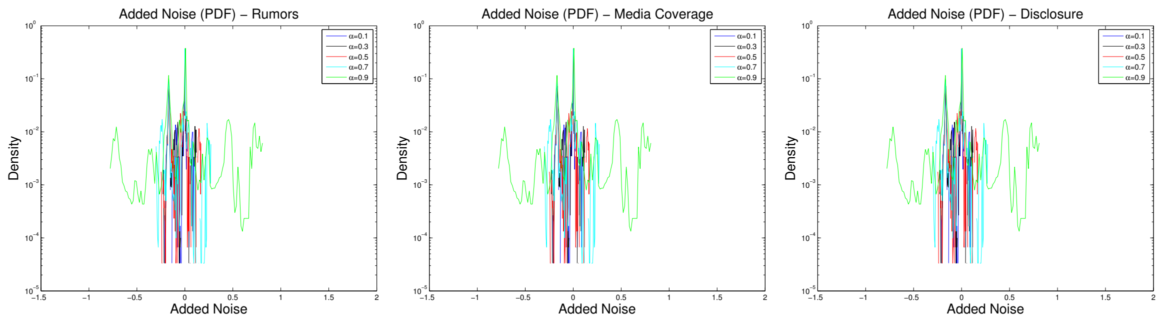

Figure 1: PDF of Added Noise (Equation 18 in the main text). Distributions are computed from values from 100 simulations, using data from each of their 300 time periods.

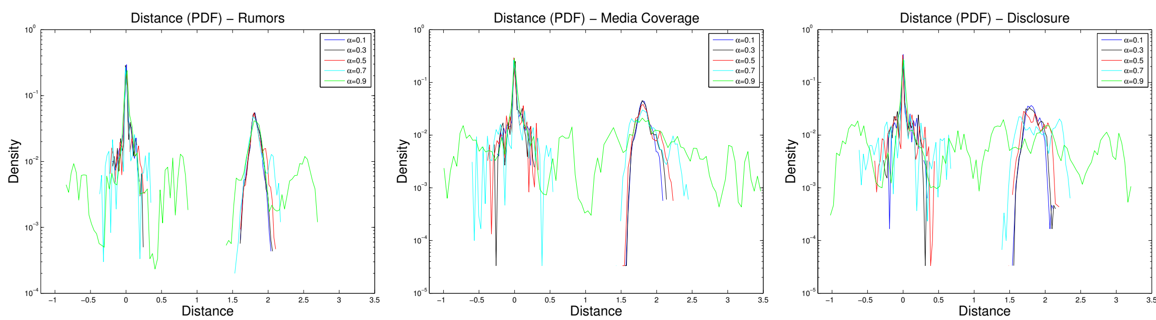

Figure 2: PDF of the Distance (Equation 20 in the main text). Distributions are computed from values from 100 simulations, using data from each of the 300 time periods.

2 Additional Figures for the Auto-correlated case

We hereby report additional figures concerning the Cumulated Distribution of several measures reported in the main text for the case of the autocorrelated news flows.

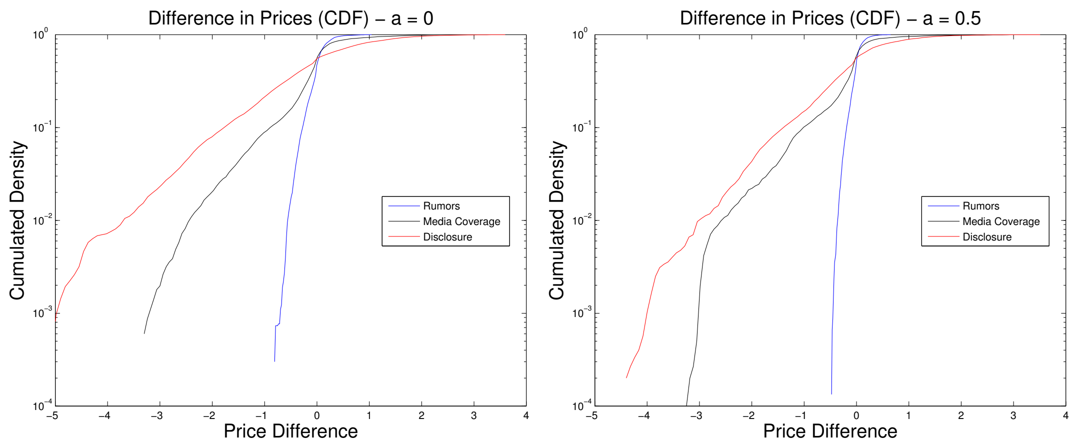

Figure 3: CDF of the Difference in prices $p_t^{with} - p_t$ (between with and without shock, on each single data) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$

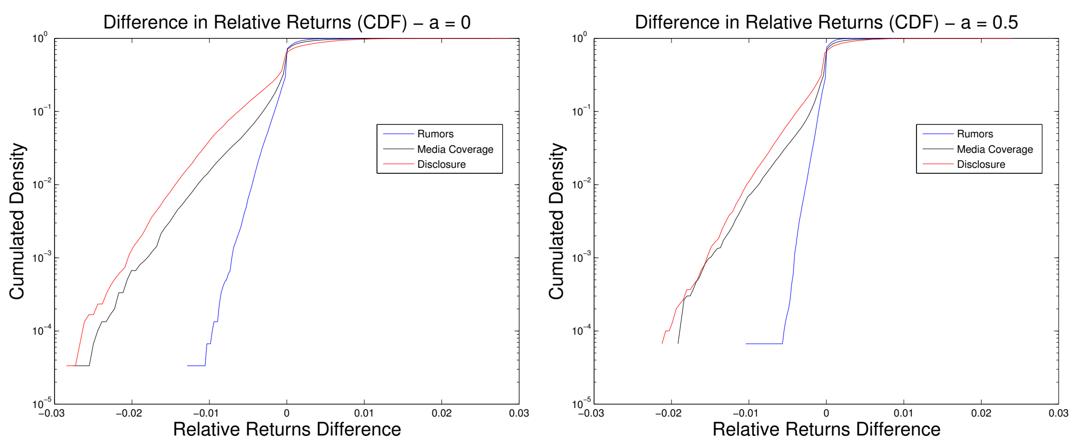

Figure 4: CDF of Difference in Relative Returns in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Relative returns are compute respectively as: $Returns_t^{with} = \frac{p_t^{with} - p_{t-1}^{with}}{p_{t-1}^{with}}$ for the case with shock and $Returns_t = \frac{p_t - p_{t-1}}{p_{t-1}}$ for the case without shock. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$.

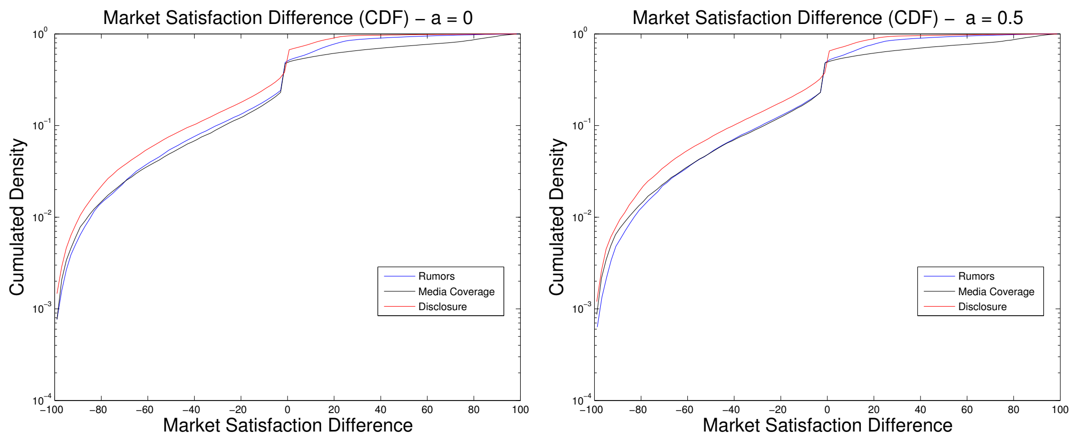

Figure 5: CDF of Difference Market Satisfaction (between the cases with and without shock), as defined in Equation 15 in the main text. Distributions are computed from 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$.

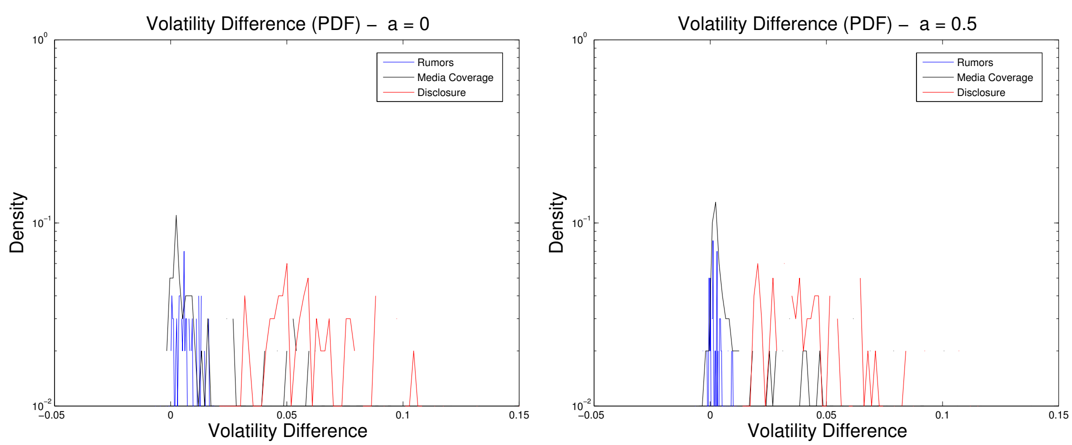

Figure 6: PDF of Market Volatility between the cases with and without shock defined respectively as $\frac{Std(p_t^{with})}{mean(p_t^{with})}$ and $\frac{Std(p_t)}{mean(p_t)}$. Distributions are computed from 100 simulations (for each combination of auto-correlation of shocks and degree of information). One value for each simulation. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$.

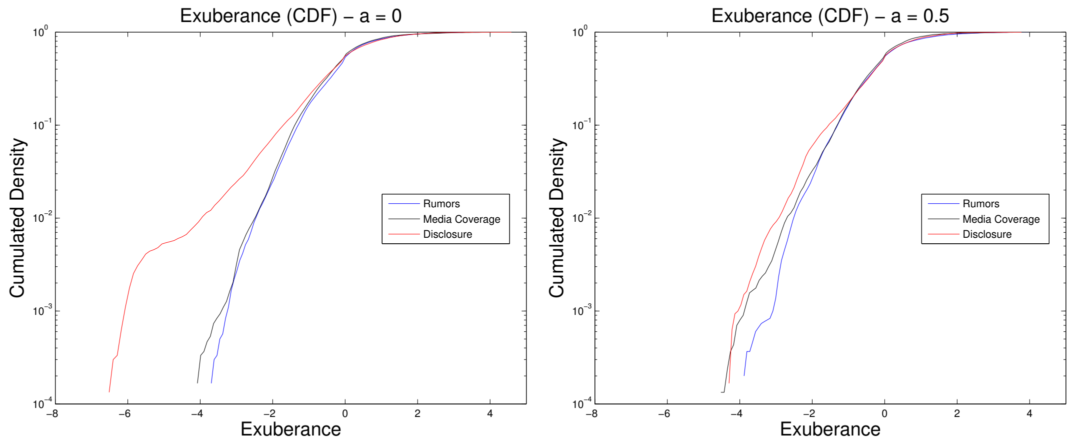

Figure 7: CDF of Exuberance in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Each Figure is a different level of autocorrelation. Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$. Exuberance is computed as: $Exub_t = p_t^{with} + p_t - NN_t$ according to Equation 16 in the main text.

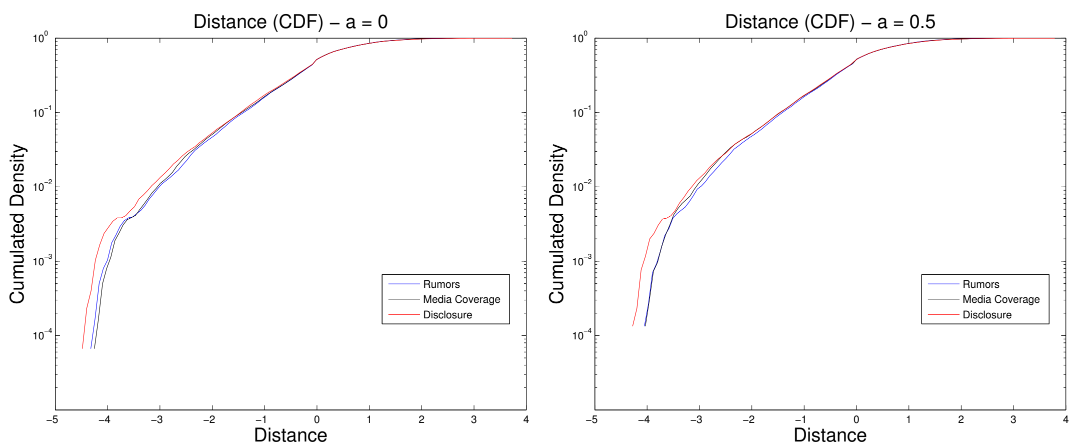

Figure 8: CDF of Distance in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Each Figure is a different level of autocorrelation. Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$. Distance is computed as: $Distance = \frac{p_t^{with} - FN_{t-1}}{FN_{t-1}}$.