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 collective market pricing mechanisms 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 is expected to 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

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paradigmatic cases of stochastic news, before generalising them to autocorrelated news. Our results are further corroborated by robustness checks over the parameter space and across several market trading mechanisms.

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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 is based 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 connections among 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, we develop 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 (2016). The model is used to study the impact of information diffusion and market microstructure over market price formation. The agent-based model is useful to analyse incomplete and evolving information diffusion across investors over time and circumstances, since it identifies each investor separately. A large set of information conditions and behavioural patterns may then be investigated, disentangling the dynamic relationship between heterogenous individual investors, their mutual interactions, and overarching social structures or institutions. Our frame of analysis generalises on existing literature, enabling to study this large set of behavioural and structural conditions under a unified framework. The latter allows to better disentangle individual and collective drivers of market informational efficiency through time and circumstances. In particular, our contribution sheds light on how departures from market informational efficiency driven by news depend on the interaction between limitedly rational trading investors, scenarios of information generation scenarios, and investor market sentiment.

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. Investors do not know or agree upon a universal notion of fundamental 'value', which would then be unique (or uniquely defined) over time and circumstances for all of them. Instead, our modelling strategy accepts that investors idiosyncratically receive and interpret distinct evolving signals of fundamental performance that jointly deliver noisy information about the security issuer. Heterogeneous investors form focal price opinions on noisy information, and pass orders through a trading facility that rules over and transforms their orders into settled transactions at ongoing market prices over time. From this institutional economic perspective, informational efficiency of market price formation crucially depends on market microstructure and 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 least at its early dissemination. Our approach expands on existing literature by disentangling individual and collective dimensions that denote market informational efficiency. The latter systemic performance depends on the ways the two collective dynamics (information generation and market microstructure) frame and shape individual interactions across investors, along with the ways heterogenous investor behaviour reacts to those dynamics. Although our investors are boundedly rational, the financial system does still generate satisfying levels of informational efficiency under full and immediate information diffusion and a balanced reaction by all the investors. When these structural and behavioural conditions are relaxed, specific patterns of informational efficiency and inefficiency occur and may then be studied by simulation analysis in scenarios of information diffusion and investor market sentiment denoted by the parameter space.

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 these 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 2016). 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 and across several market trading mechanisms adapted from Anufriev and Panchenko (2009). 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).

1 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. This type of model is useful to analyse incomplete and evolving information diffusion across investors over time and circumstances, since it allows to identify each investor individually and to consider its separately. A large set of information conditions and behavioural patterns may then be investigated, disentangling both the ways in which information spreads among investors, and the ways in which it is interpreted by them over time and circumstances.

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:

$$E_{i,j,t}(p_{t+1}) = p_t + \alpha_{j,t}(p_t - p_{t-1}) - \beta_{i,j,t}\left(E_{i,j,t-1}(p_t) - p_t\right) + \gamma_{i,j,t}\phi_i F_t + I_{i,t}\Delta_{i,t}N_t$$
$$\forall i \in [0,1], \forall j \subset (D;S), \forall t, \text{ with } I_{i,t} = \{0;1\} \text{ and } \Delta \in [0,1] \qquad (1)$$

This focal price expectation formulation internalises both chartist and fundamentalist strategies. From a theoretical perspective, this implies that neither investors nor their strategies are forced to be of one type or another. All and every investor is concerned with both strategies and decides how to include them in its focal price decision over time and circumstances. 'Fundamentalist' investors may then consider profit opportunities related to market momentum (market price trend), while 'chartist' investors may consider some background price reference (fundamental signal), when forming their expectations. Heuristically speaking, this formulation does further point to diversification of investment portfolios between trading and holding portfolio subsets. Moreover, the focal price expectation parameters - which are normalised to one - are free and may then evolve over time and also be dependent on each other. Furthermore, this formulation includes a news signal that may be heterogeneously known and interpreted across investors, time and circumstances. For informed investors, this news signal integrates the publicly available one about the fundamental performance of the security issuer whose securities are traded.

Analytically, 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 expectation revision, which 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, weighted by $\beta_{i,t}$. 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. These signals are 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 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. According to the baseline market trading protocol, 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:

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

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

$$p_{t+1} = \begin{cases} p^{NC} = median(E_{i,t}(p_t)) & \text{if } \overline{P}_{S,t} \leq \underline{P}_{D,t} \\ \\ p^{C} = \frac{\overline{P}_{S,t}(\overline{P}_{D,t} - \underline{P}_{D,t}) + \underline{P}_{D,t}(\overline{P}_{S,t} - \underline{P}_{S,t})}{(\overline{P}_{S,t} - \underline{P}_{S,t}) + (\overline{P}_{D,t} - \underline{P}_{D,t})} & \text{if } \overline{P}_{S,t} \geq \underline{P}_{D,t} \end{cases} \tag{2}$$

With:

$$\begin{aligned} \overline{P}_{S,t} &= max[E_{i=0,S,t}(p_{t+1}); E_{i=1,S,t}(p_{t+1})] \\ \underline{P}_{S,t} &= min[E_{i=0,S,t}(p_{t+1}); E_{i=1,S,t}(p_{t+1})] \\ \overline{P}_{D,t} &= max[E_{i=0,D,t}(p_{t+1}); E_{i=1,D,t}(p_{t+1})] \\ \underline{P}_{D,t} &= min[E_{i=0,D,t}(p_{t+1}); E_{i=1,D,t}(p_{t+1})] \end{aligned} \tag{3}$$

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 2 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 (Equation 3). 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. This latter assumption implies that the market mechanism follows the orders, seeking for matching across them. When matching does not occur, the market mechanism fixes the market price at the middle of expressed price orders, where potential matching would be the highest, in order to facilitate market price formation in the successive period.

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. Since our analysis focuses on the relative impact of the news flows and shocks over the market price series, it is compelling to further test it for alternative market mechanism designs, to assess the robustness of our findings across the latter. Therefore, we replicate the market designs developed by Anufriev and Panchenko (2009) in Section 4, and test our protocol across them. Main results prove to be robust across various market trading mechanisms, namely, Walrasian auction, market maker, batch auction and order book.

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 2016).

2 Simulation Calibration

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

$$\begin{gathered} \{F_{t=0} = F_0; F_{t>0} = \epsilon_1\} \\ N_t = N_{shock} + (1-a)\epsilon_2 + aN_{t-1}; \end{gathered} \tag{4}$$

where $N_{shock} \gg F_t$ when it exists, and 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 characterize the information diffusion process through media and social 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:

$$FN_t = \sum_t (F_t + N_t) \ \forall t \quad \text{or equivalently} \quad FN_t = FF_t + NN_t \ \forall t \tag{5}$$

Where:

$$FF_t = \sum_t F_t \quad \text{and} \quad NN_t = \sum_t N_t$$

The intrinsically chaotic dynamics prevents the actual market pricing process to provide a perfect alignment at each moment of time. However, given our calibration, an 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, an informational shock N_t contains some value content that is perceived by informed investors 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 persistent 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 window.

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 $\alpha_{i,t} \in [0,1]$ (0.5 being the baseline); signalling source N_t confidence $\Delta_{i,t} \in [0,1]$ (0.5 being the baseline); and forecasting error weight $\beta_{i,t} \in [0,1]$ (0.5 being the baseline). In particular, we maintain that confidence in the signalling source F_t is uniform ($\phi_i \sim U\,[0,1]$) and centered to 0.5 (i.e. $\gamma_{i,t} = 1\ \forall i,t$). 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 connects all relevant market price movements with the signalling source N_t whose impact is under investigation. Its purpose is then to comparatively assess the relative impact of the news flows and shocks on the market price series under the large set of circumstances subsumed by the parameter space. Brock and Hommes (1998) and others develop models where expectation parameters evolve and are updated over time. However, given that our analysis is focused on the market impact of information diffusion, for sake of clarity in the comparative analysis, we scope out expectation parameters update that may depend on switching mechanisms based upon profitability or fitness. In particular, we assume that ϕ_i, and $\gamma_{i,t}$ are exogenous. This allows us to attribute all the simulation variability to the news and its diffusion.

According to our framework of analysis, investors trade on disagreement: an 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.

Our simulation approach entails three parts. First, we run simulations through a baseline case of stochastic informational news N_t patterns. We apply the same time window for all 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).

The second part of the analysis generalises our analysis through autocorrelated informational news N_t patterns. In this part, the time window of autocorrelated news shocks 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 features 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 measures of financial systemic performance over the full range of the share of informed investors $SI \in [0; 1]$ and the degree of speculative attitudes $\alpha_{i,t} \in [0, 1]$.

The third part of our simulation analysis corroborates our main findings across several market trading mechanisms used in the literature. In particular, adapting from Anufriev and Panchenko (2009), namely, Walrasian auction, market maker, batch auction and order book.

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 (where p_t^w and p_t denote the price series formed respectively with and without activation of the informational shock N_t). 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.

We first study two temporal evolution regimes of informational shock patterns: one *stochastic news* flow characterized by a single announcement whose effect persists over time; another *autocorrelated news* flow that features reverberation effects over time.. 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 follows Equation 4 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 $a = 0$) which denotes informational shocks as random walks.

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. Heuristically speaking, this scenario refers to provision of regulated information through financial reporting and disclosure;

- **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. Heuristically speaking, this scenario refers to media coverage by specialised newspapers, tv channels and social media, where expert opinions are discussed and disseminated;

- **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. Heuristically, this scenario refers to informal social interaction among professionals interested in trade and investment, including private communication of confidential and privileged information.

3 Simulation Results

This section summarises our simulation results for stochastic informational shock patterns (Section 3.1) and autocorrelated informational shock patterns (Section 3.2). 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 Section 3.1 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 price series without and with news flow:

$$\text{Price difference}_t = p_t - p_{t-1} \tag{6}$$

$$\text{Price return}_t = \frac{p_t - p_{t-1}}{p_{t-1}}. \tag{7}$$

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:

$$\text{Market volatility} = \frac{Std(p_t)}{Mean(p_t)}. \tag{8}$$

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:

$$\text{Mkt}_{\text{satisfaction}}(t) = \frac{min(\text{size}(D_t), \text{size}(S_t)) \cdot 100}{max(\text{size}(S_t), \text{size}(D_t))}. \tag{9}$$

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 was labelled 'market vagary' by (Biondi and Righi 2016). It is labelled 'market errance' hereafter to stress its persistent misalignment with existing evidence of fundamental performance as provided by information sources FF_t and NN_t. We assess this quality through some descriptive statistics, computed in or compared between the two distinctive cases without and with news flow.

In particular, Exuberance ($Exub_t$), denotes the difference between the price with and without the shock N_t (respectively p_t^w and p_t), and the cumulated news NN_t as follows:

$$Exub_t = p_t^w - p_t - NN_t \ \ \forall t \tag{10}$$

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:

$$\text{Total Absolute Exuberance} = \sum_t |Exub_t| \tag{11}$$

Market exuberance points to the capacity of the market price series to incorporate 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:

$$\text{AddedNoise}_t = \left| \frac{p_t^w}{FF_t + NN_t} - \frac{p_t}{FF_t} \right| \tag{12}$$

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 as follows:

$$\text{Total Added Noise} = \sum_t |\text{AddedNoise}_t| \tag{13}$$

We also introduce the following descriptive statistics of distance:

$$\text{Distance}_t = \frac{p_t^w - FN_{t-1}}{FN_{t-1}} \tag{14}$$

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

The rest of this section analyses the evolutionary pattern of these 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 $\alpha_{i,t} = \alpha$ that each investor attributes at each time step 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 2016). In particular, when $\alpha \to 0$ and $\alpha < 0.5$, investors tend to disregard the market trend signal, denoting fundamentalist (conservative) attitudes. Vice-versa, when $\alpha \to 1$ and $\alpha > 0.5$, investor tend to overvalue the market trend signal, denoting speculative attitudes. The combination of these structural and behavioural conditions (respectively, the information diffusion regimes and the investor market sentiment) enables to study the market performance (especially its market informational efficiency) in different scenarios.

3.1 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.

The following subsections summarise simulation analyses for market pricing quality (3.1.1), prices and returns (3.1.2), market liquidity and volatility (3.1.3) and market informational efficiency (3.1.4). The first analysis points to the overall market capacity to provide a good approximation of the fundamental performance through time. The further analyses show financial system performance under combination of behavioural and structural conditions. In particular, behavioural conditions are denoted by investor market sentiment $\alpha_{i,t} = \alpha$ and structural conditions are denoted by featured information diffusion regimes (rumors; media report; disclosure).

3.1.1 Market pricing quality

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. The financial system's possible behaviours can be categorized in three mutually exclusive scenarios. Market pricing quality refers to the comovement of the market price series with the fundamental benchmark series. In turn, this comovement refers to the first and second moments of the fundamental series. To be sure, the fundamental benchmark series generates an intrinsic dynamic (first moment) that has its own evolution over time, delivering an intrinsic noise related to its own variance (second moment).

In the 'satisfying' scenario, the market price series remains satisfyingly near to the fundamental benchmark series over time. We consider the market price series as 'satisfying' when its first and second moments remain relatively close to those of the fundamental benchmark series. This implies that the market price is a good estimate of the fundamental series; it does not add excess volatility to the underlying fundamental series; and temporary shocks are quickly and smoothly reabsorbed. At the opposite extreme with respect to the satisfying scenario is the 'errant' scenario (Biondi and Righi 2016), where the market price series shows permanent departure from the fundamental benchmark series over time. Finally, in the 'exuberant' scenario (Shiller 2002), the market price series shows material but transient departure from the fundamental benchmark series over time. To be sure, errancy points to disalignment in the first moments of the series, while exuberance points to disalignment in the second moment of them. In both cases, in fact, the current market price cannot be considered as a good estimate of the fundamental performance of reference.

Our simulation calibration allows disentangling these three scenarios by focusing on Exuberance ($Exub_t$) as defined in Equation 10. 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 $N_{shock} = 2$) as follows:

$$\bar{\epsilon} = 2 \cdot |\max(F) + \max(N_{N \neq N_{shock}})|. \tag{15}$$

This benchmark implies that a market price is considered to diverge from the fundamental signal of reference only when it materially deviates from the maximal drift generated by F and N flows.

Using the benchmark in Equation 15, we apply a three-steps algorithm to classify each market price series according to the flowchart in Figure 1.

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% the last periods of the time window (C) remains larger than the benchmark level epsilon. Formally, the market price series is considered errant iff: $\overline{(|Exub_{290 \leq t \leq 300})}| > \bar{\epsilon}$.

If a market series is not errant, it is considered 'exuberant' when, during the time phases 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. Formally this corresponds to define a market price series as exuberant iff

$$\sum_{t \in B} u_t > 0.1 L_B \vee \sum_{t \in C} u_t > 0.1 L_C,$$

where L_B and L_C are the lengths in time periods of the time phases B and C, and:

$$u_t = \begin{cases} 1 & \text{if } |Exub_t| > \bar{\epsilon} \\ 0 & \text{otherwise.} \end{cases} \tag{16}$$

A market price series is finally, 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 progressively change the level of information diffusion between 1% and 100% and we run 100 simulations for each level. Figure 2 summarises simulation results reporting the percentage of cases of the different types emerging. In a majority of cases, the market price series does not consistently align with the benchmark level of reference, showing 'errant' or 'exuberant' behaviour. This result is not consistently improved by information diffusion, since market price series quality oscillates when the share of informed investors IS increases. Only at the hypothetical level when all the investors are fully informed (i.e., when $IS = 1$), the majority of market price series becomes 'satisfying'. Observing the relationship between the percentage of informed and the market outcome, a non monotone relationship emerges. When less than half of the individuals are informed, the market is frequently able, in the long run, to re-absorb the misalignments with the fundamental value (leading to relatively more cases of exuberant behaviour). However when more than half of the individual are informed about the transient news, the misalignment becomes permanent more often, leading to a prevalence of errant behaviour.

This result makes fully efficient market efficiency becoming 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.

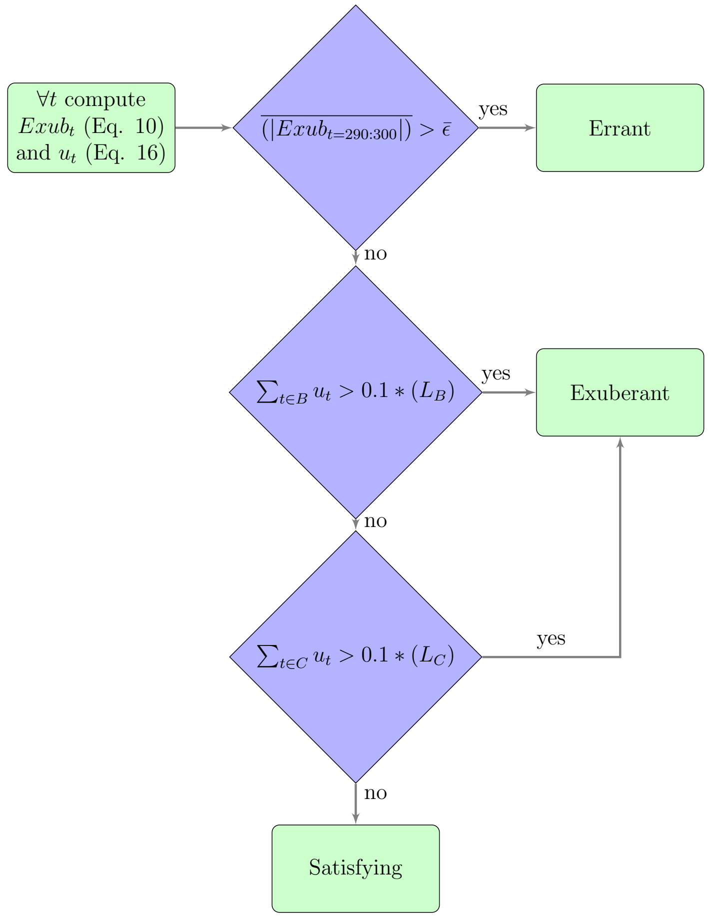

Figure 1: The market pricing quality classification algorithm of market price series between 'errant', 'exuberant' and 'satisfying'. u_t are computed according to Equation 16, while L_B and L_C are the lengths in time periods of the time phases B and C respectively.

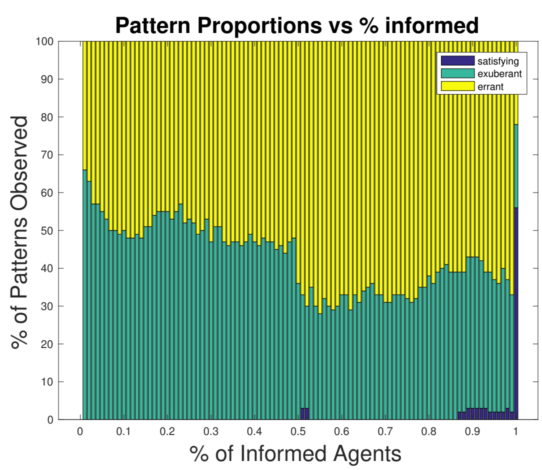

Figure 2: For each given share of informed investors we run 100 simulations counting how many turn out to be of type 'satisfying', 'errant', and 'exuberant'. We plot the proportions with respect to the share of informed investors. The three types are mutually exclusive. Definitions are provided in the main text in Section 3.1.1 and Figure 1.

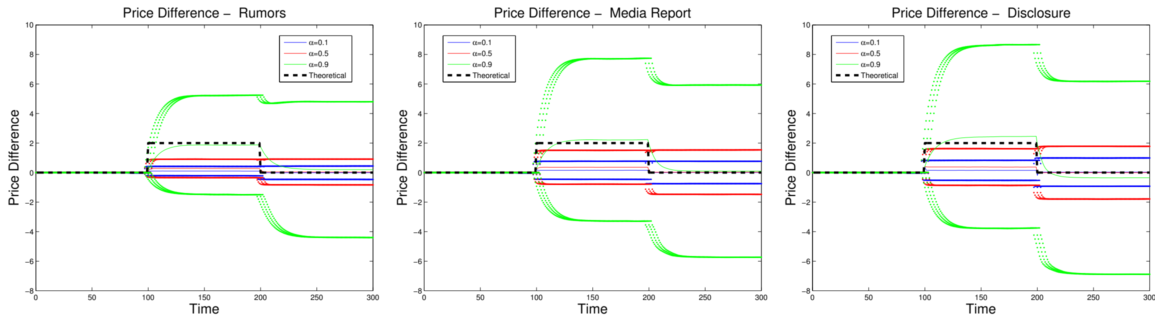

Figure 3: Temporal structure of price difference between cases with and without shock: $p_t^w - p_t \ \forall t$. Mean and Standard Deviation from 100 simulations of 300 periods are reported for each time period.

3.1.2 Prices and Returns

We analyse here the temporal structure of the price difference between cases with and without informational shock (Figure 3), his CDF (Figure 5), the temporal structure of returns (Equation 7) with informational shock (Figure 4), and the CDF of the difference in relative returns between cases with and without shock (Figure 6).

Speculative attitudes consistently increase the dispersion of prices across the CDFs under 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 attitudes tend to further widen this range, while conservative attitudes tend to reduce it, under all the information diffusion (Figures 3 and 5). 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 4). 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 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.

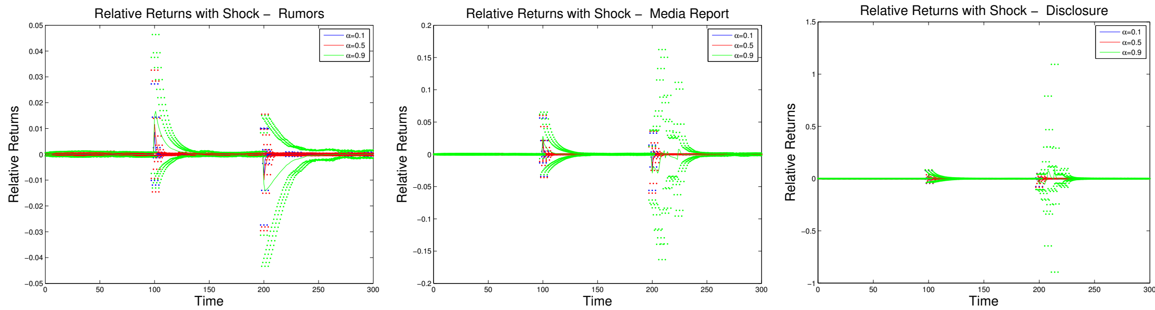

Figure 4: Temporal structure of relative returns (case with shock). Returns are defined in Equation 7 Mean and Standard Deviation from 100 simulations of 300 periods are reported for each time period.

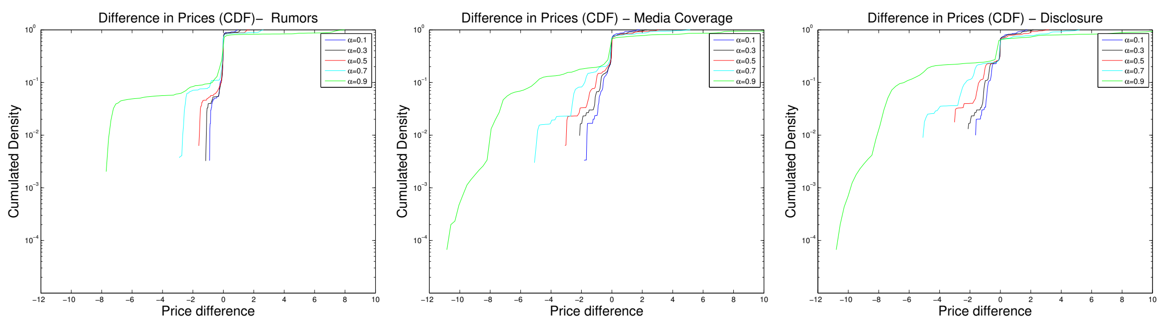

Figure 5: CDF of price difference between cases with and without shock: $p_t^w - p_t$. The CDF is computed plotting together data from 100 simulations, each 300 time periods long.

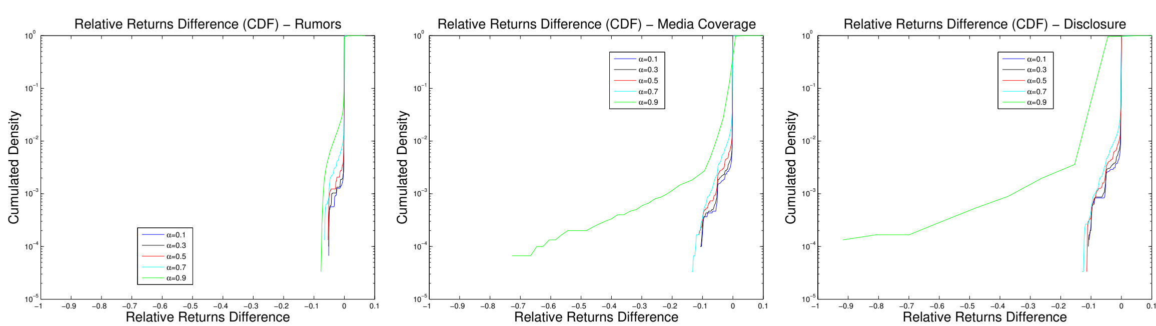

Figure 6: CDF of Difference between cases with and without shock on Relative Returns. Relative Returns (Equation 7) are defined respectively as: $\frac{p_t^w - p_{t-1}^w}{p_{t-1}^w}$ for the case with shock and $\frac{p_t - p_{t-1}}{p_{t-1}}$ for the case without shocks. Distributions are computed for 100 simulations, each providing data for 300 time periods.

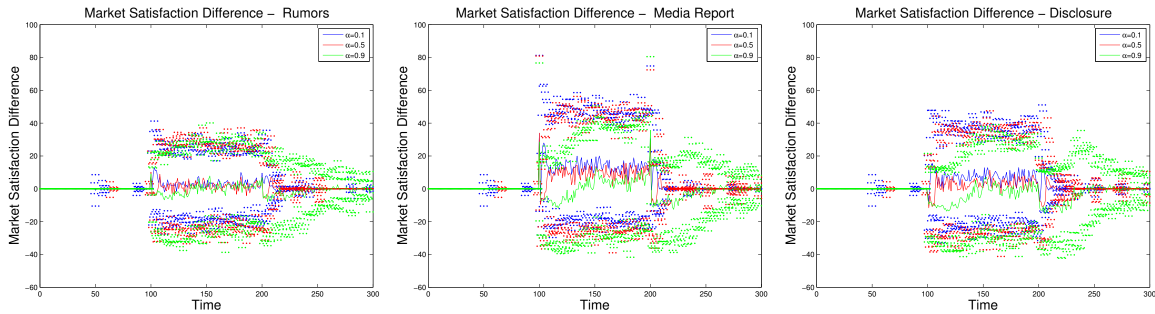

Figure 7: Temporal structure of market satisfaction difference between cases with and without shock. Market satisfaction is computed according to Equation 9. Mean and Standard Deviation from 100 simulations of 300 periods are reported for each time period.

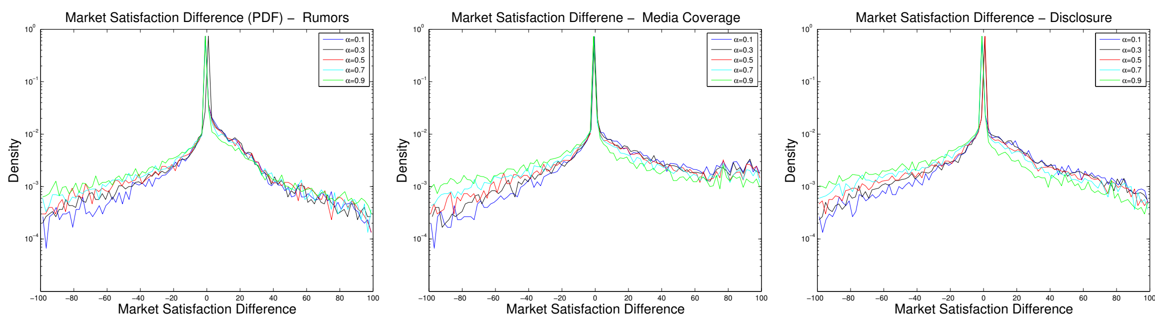

Figure 8: Distribution of Market satisfaction (Eq. 9) difference between case with and without shock. Distributions are computed for 100 simulations, each providing data for 300 time periods.

Moreover, speculative attitudes tend to further widen the relative returns width, while conservative attitudes tend to reduce it (Figure 5). 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 6), since news diffusion increases heterogeneity, facilitating market order satisfaction.

3.1.3 Market satisfaction and Volatility

The variance of market satisfaction (Figure 7) is 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 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

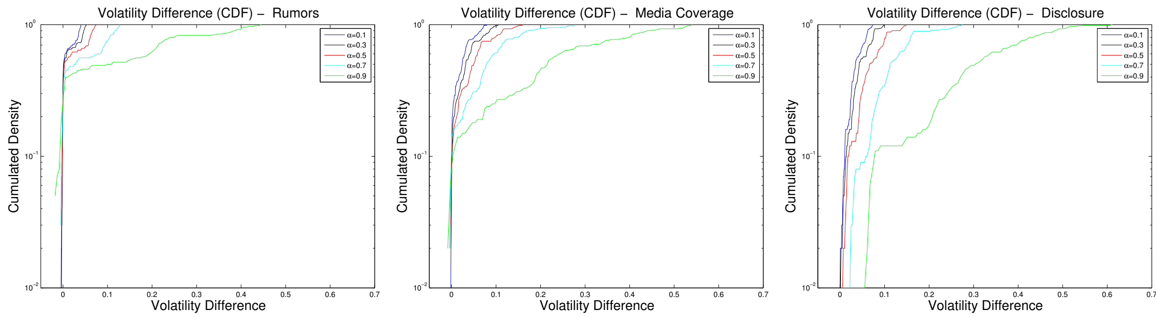

Figure 9: CDF of volatility difference between cases with and without shock. Volatility is defined according to Equation 8. Distributions are computed considering the difference of the volatility expressed in 100 simulations.

suggest that the introduction of an information source 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 an interesting response to speculative attitudes as captured by higher values of parameter α (Biondi and Righi 2016). 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 the news flow shock (Figure 8), as shown by the different distribution shapes under the various news scenarios (rumors, media coverage and disclosure). This finding implies endogenous generation of market illiquidity when speculative attitudes dominate investor expectations (see also Biondi and Righi 2016).

Market volatility is of course always increased by the informational shock, with its increase showing a fat tailed distribution (Figure 9). These tails are exacerbated by speculative attitudes, while are reduced by conservative attitudes in investors, behaviour. Under all the information diffusion scenarios, volatility increases along with α, especially under speculative attitudes when $\alpha \gg 0.5$. It is also significant that volatility increases consistently with larger information diffusion IS, confirming its dependency on the overarching informational process.

3.1.4 Market informational efficiency

Concerning our measure of added noise (Equation 12), under the three scenarios (Figures 10), conservative attitudes (when $\alpha < 0.5$) tend to decrease relative added noise, while speculative attitudes (when $\alpha > 0.5$) increase it relative to balanced attitudes (when $\alpha = 0.5$). However, speculative attitudes clearly enhance relative added noise showing extreme events in the

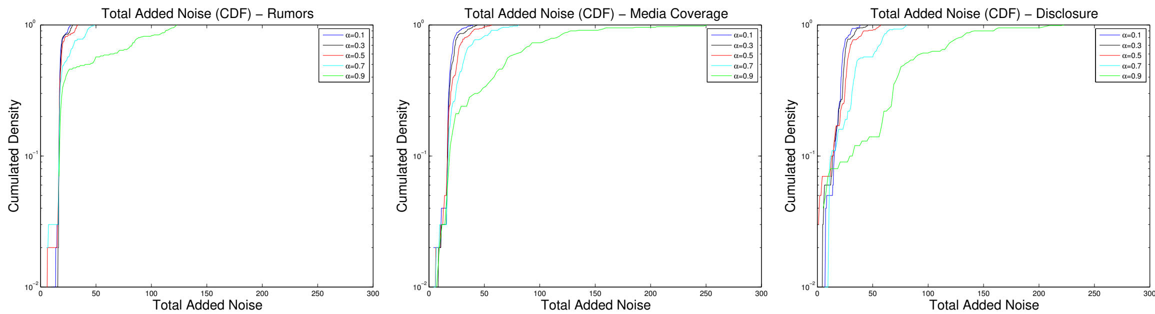

Figure 10: CDF of Total Added Noise (Equation 13). Distributions are computed from values from 100 simulations, using data from time steps 100 onwards.

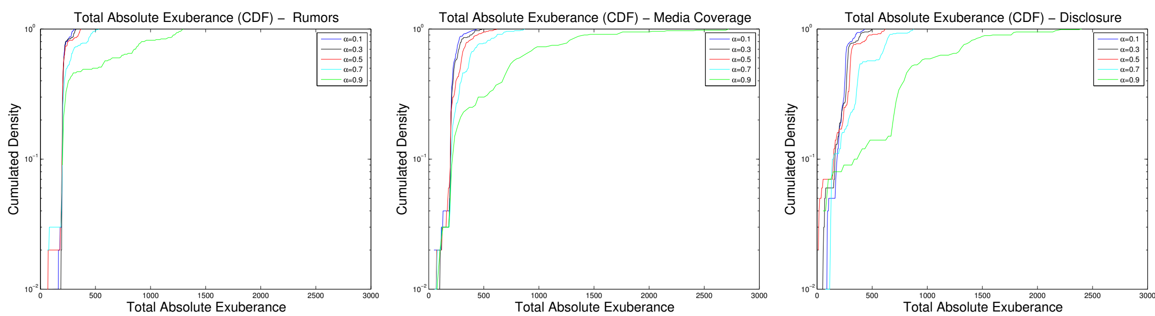

Figure 11: CDF of Total Absolute exuberance (Equation 11). Distributions are computed from values from 100 simulations, using data from each of the 300 time periods.

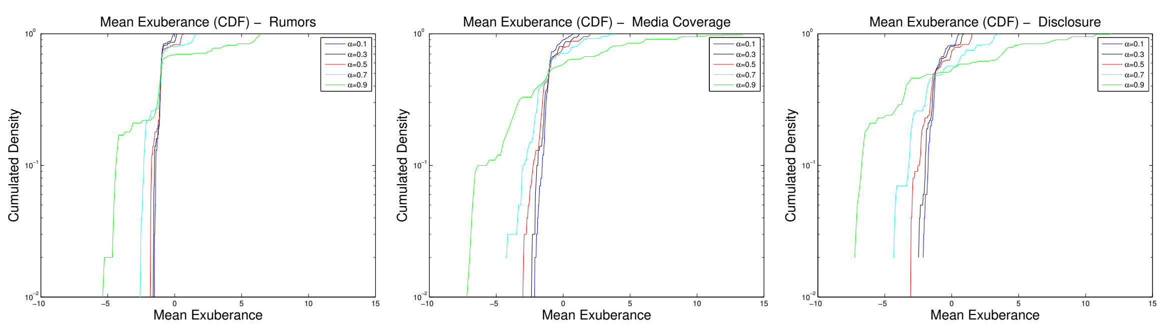

Figure 12: Average Exuberance computed as $\overline{Exub} = mean(Exub_{t \geq 100})$, where $Exub_t = p_t^w - p_t - NN_t$.

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 11 (Figure 11). Again, under all the information diffusion scenarios, this measure is reduced by conservative attitudes (which remain near to the balanced case when $\alpha = 0.5$), while speculative attitudes (when $\alpha \to 1$ and $\alpha > 0.5$) exacerbate total absolute exuberance showing extreme positive events.

Our measure of average exuberance (Figure 12) 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 α 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.

3.2 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 the new case, the news is active from $t = 0$ and $t = 290$, and there is no large jump in the value of the news but a series of small auto-correlated changes through time[1]. 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 is fixed at its central level of $\Delta_{i,t} = 0.5$ for all the investors. Moreover, investors are featured by neutral market mood ($\alpha = 0.5$), meaning that they are neither speculative nor conservative in their collective opinion on the market price trend $p_t - p_{t-1}$.

3.2.1 Market pricing quality

In order to extend and corroborate our simulation results under stochastic news flow, we adopt the same classification algorithm presented in Section 3.1.1 and Figure 1 to study the

[1]Since the news flow shock N_t disappears by $t = 290$, the market price series p_t and the fundamental signal FF_t are supposed to converge during the last 10 periods ($290 \leq t \leq 300$).

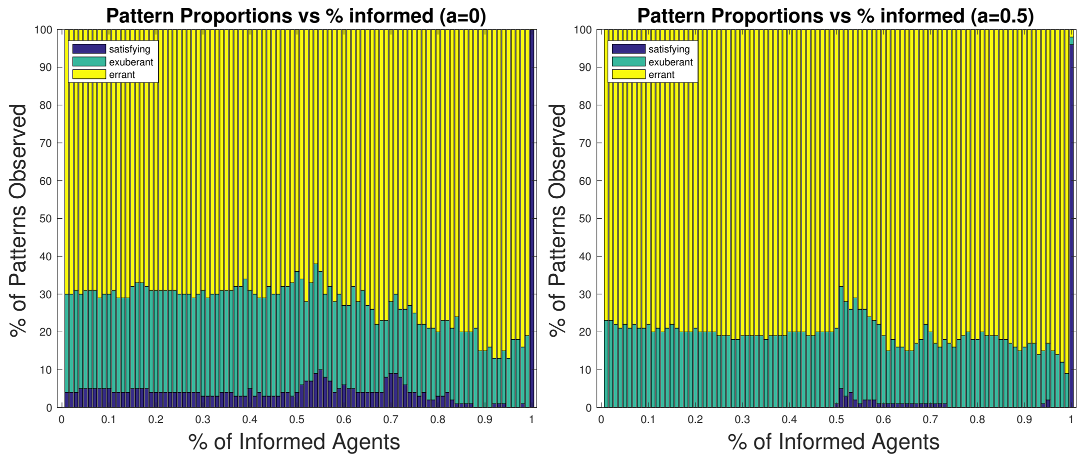

Figure 13: For each given share of informed investors we run 100 simulations counting how many turn out to be of type 'satyfactory', 'errant', and 'exuberant'. We plot the proportions with respect to the share of informed investors. The three types are mutually exclusive. Definitions are provided in the main text in Section 3.1.1 and Figure 1.

market informational efficiency under autocorrelated news flow.

Our simulation results with autocorrelated news flow (Figure 13) 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 13). For $a = 0$ we observe a tendency of the proportion of exuberant cases to decrease along with the proportion of informed agents.

3.2.2 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 5 in supplementary material) and returns (Figure 14). Fat tails under the disclosure scenario seem to be reduced by autocorrelation, which tends then to align this scenario with the media coverage. Autocorrelation decreases the dispersion of the prices when information diffusion is large, when investors are widely and uniformly informed and hold neutral speculative expectations neutral ($\alpha = 0.5$).

However, information diffusion appears to have a negative quality impact on both series, reinforcing the presence of extreme events that feature market prices divergent from the

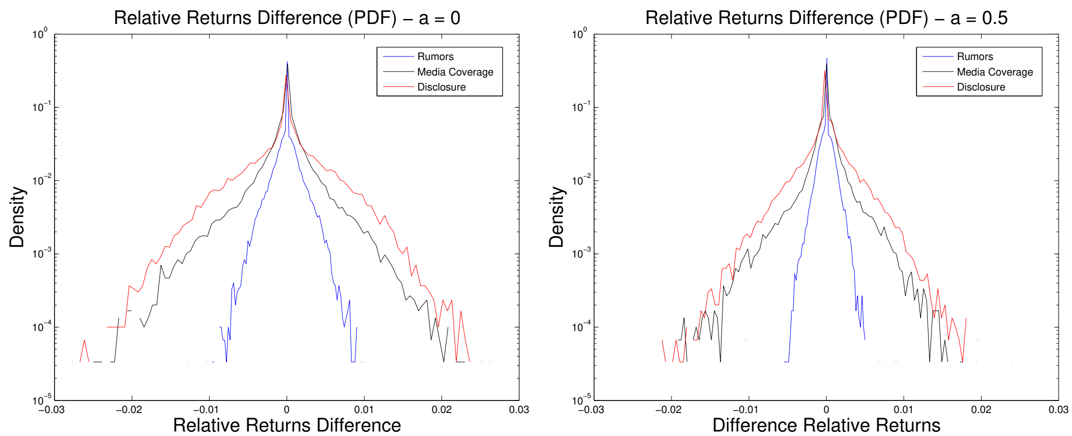

Figure 14: PDF of Difference in Relative Returns (between with and without shock, on each single data) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Relative returns are compute respectively as: $Returns^w_t = \frac{p^w_t - p^w_{t-1}}{p^w_{t-1}}$ 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 $a = 0.5$

reference central benchmark. Under the disclosure scenario, larger information diffusion appear to reduce extreme negative reactions in both series, without reshaping the overall distribution structure.

3.2.3 Market satisfaction and Volatility

Concerning market satisfaction (Figure 15), 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 the probability of an increase in market satisfaction due to shock is higher. 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 16), the news tends to increase volatility under all kind of news flows. This impact is exacerbated by information diffusion, as when more investors know and react to the news they end up reshaping the market pricing process by incorporating the ongoing news flow in their orders.

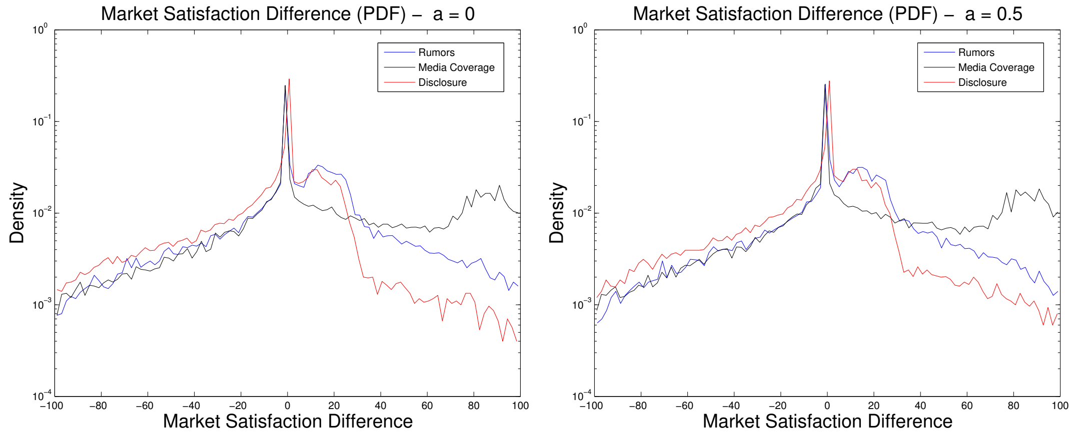

Figure 15: PDF of Difference Market Satisfaction (between the cases with and without shock), as defined in Equation 9. Distributions are computed from 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$

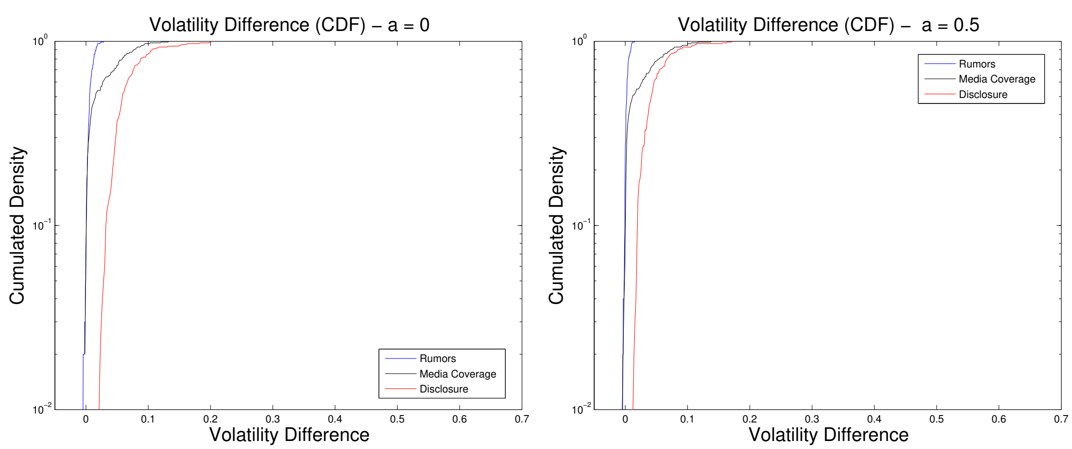

Figure 16: CDF of Market Volatility between the cases with and without shock defined respectively as $\frac{Std(p_t^w)}{mean(p_t^w)}$ and $\frac{Std(p_t)}{mean(p_t)}$. Distributions are computed from 100 simulations (for each combination of auto-correlation of shocks and degree of information). One value for each simulation. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$.

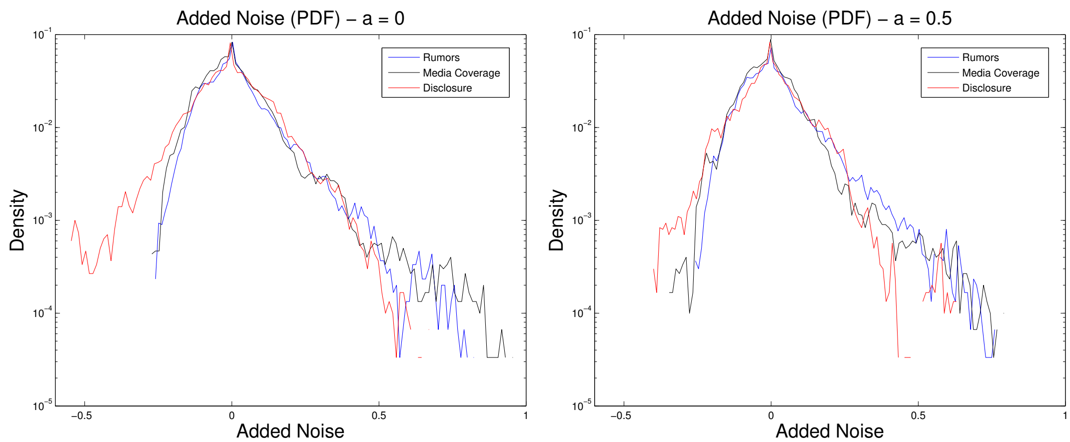

Figure 17: Added noise (Eq. 12) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$

3.2.4 Market informational efficiency

The capacity of market pricing process to align with the ongoing reference benchmark denoted by FN_t over time (Equation 5) relates to market exuberance and errancy. This phenomenon is captured here by descriptive statistics of exuberance (Equation 10), added noise (Equation 12) and distance (Equation 14). Concerning relative added noise (Figure 17 and Figure 18), 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 exuberance (Figure 19). 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. Indeed, occurrences of strong negative exuberance tend to disappear. This corroborates the positive effect of reverberation when investors are widely and uniformly informed and hold neutral speculative expectations neutral ($\alpha = 0.5$).

Concerning distance (Figure 20), 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.

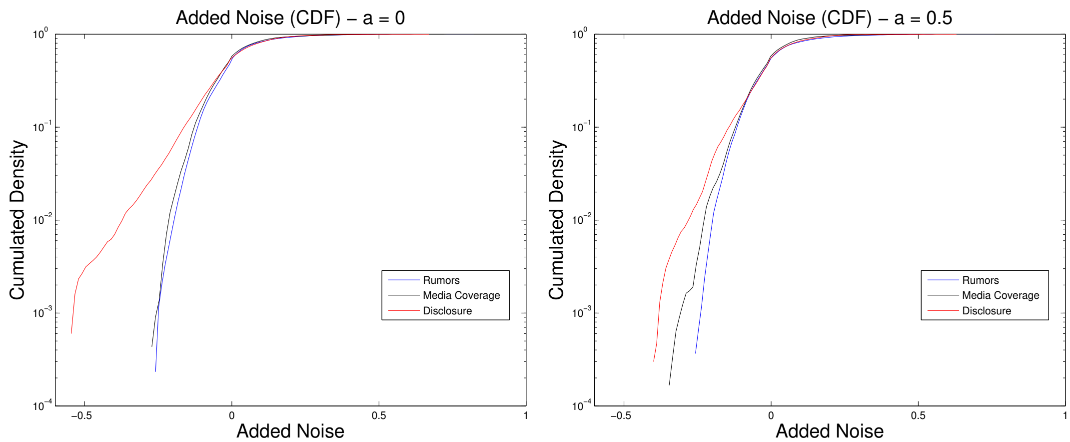

Figure 18: CDF of Added Noise (Eq. 12) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$

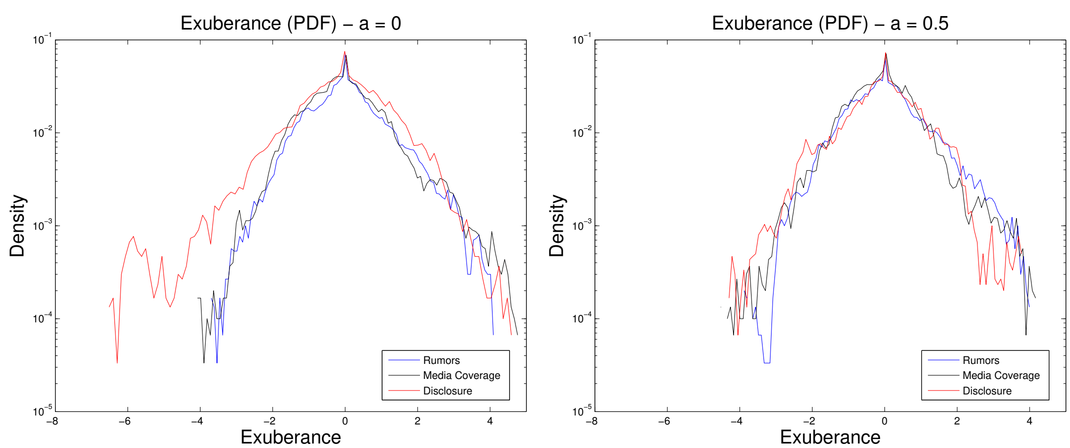

Figure 19: PDF of Exuberance in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Each Figure is a different level of autocorrelation. Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$. Exuberance is computed as: $Exub_t = p_t^w - p_t - NN_t$ according to Equation 6

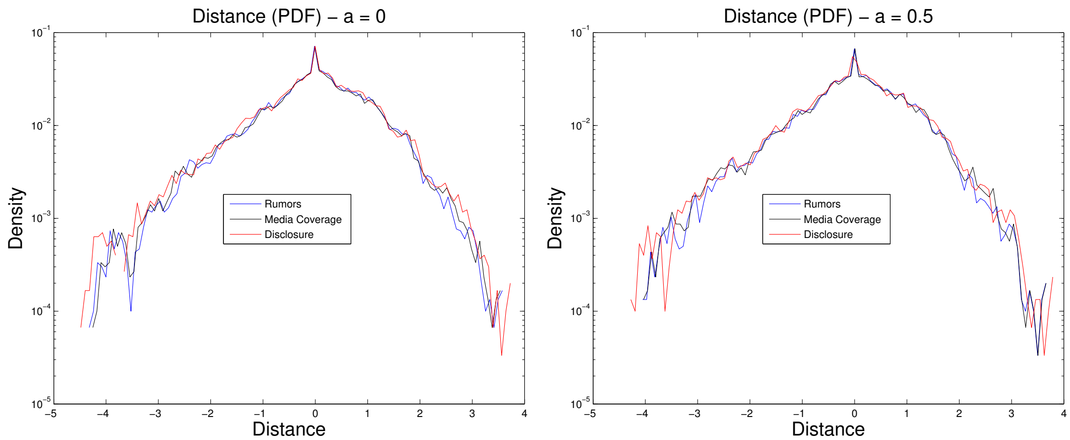

Figure 20: PDF of Distance in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Each Figure is a different level of autocorrelation. Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$. Distance is computed as: $Distance = \frac{p_t^w - FN_{t-1}}{FN_{t-1}}$.

4 Robustness across alternative trading mechanisms

According to our frame of analysis, the market pricing process depends both on the relative impact of the news flow and shocks, and on the market microstructure that aggregates and possibly satisfies individual trade orders through periods. It is therefore compelling to further test our findings under alternative market trading mechanisms, to assess their robustness. For this purpose, we adapt several market trading protocols developed by Anufriev and Panchenko (2009), to analyse the formation of market prices under them in case of auto-correlated news flow as introduced in Section 3.2. Four market trading mechanisms are tested, namely: Walrasian auction, market maker, batch auction and order book (details on the implementation of these market protocols - as well as results concerning all indicators studied in the rest of the paper - are discussed in the supplementary material).

4.1 Simulation results

To test robustness of our findings across various market mechanisms, we run simulations under auto-correlated informational shock patterns as introduced in Section 3.2. In particular, we compare some descriptive statistics (with autocorrelation parameter fixed at $a = 0.5$), under the three scenarios of information diffusion: disclosure; media coverage; and rumours. Further descriptive statistics and the case without autocorrelation ($a = 0$) are provided in supplementary material.

We consider comparative findings for market pricing quality through market informational efficiency (Figure 21) and relative returns difference (Figure 22), and for market exuberance through measures of added noise (Figure 23) and distance (Figure 24).

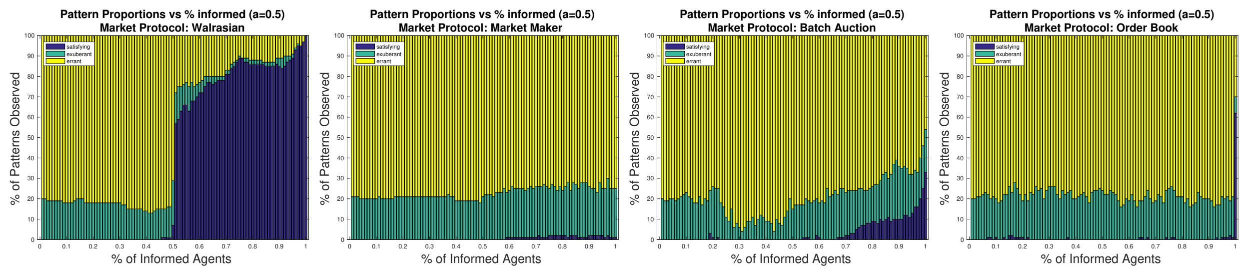

Figure 21: Market informational efficiency with respect to proportion of informed investors (see Section 3.1). Autocorrelation is $a = 0.5$. Market protocols: Walrasian (First Panel from the left), Market Maker (Second Panel), Batch Auction (Third Panel), Order Book (Right Panel).

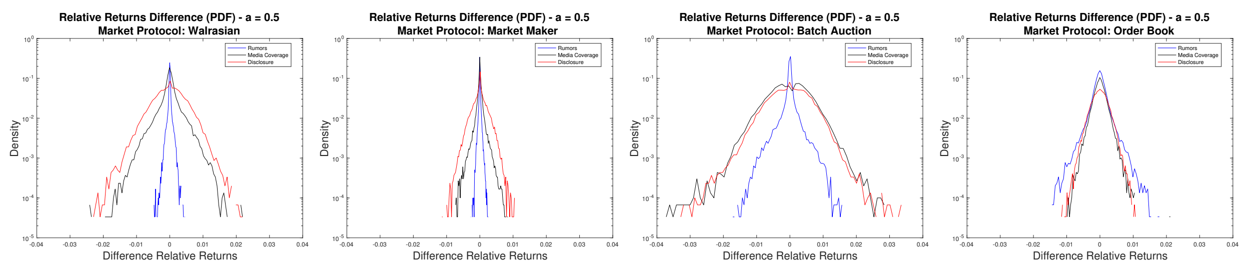

Figure 22: Distribution of Relative returns (Equation 7) difference with autocorrelation $a = 0.5$. Market protocols: Walrasian (First Panel from the left), Market Maker (Second Panel), Batch Auction (Third Panel), Order Book (Right Panel).

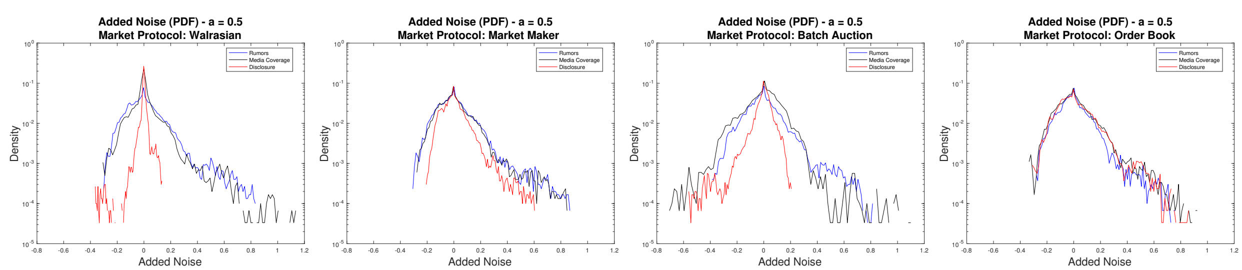

Figure 23: Distribution of Added noise (Equation 12) with auto-correlation $a = 0.5$. Market protocols: Walrasian (First Panel from the left), Market Maker (Second Panel), Batch Auction (Third Panel), Order Book (Right Panel).

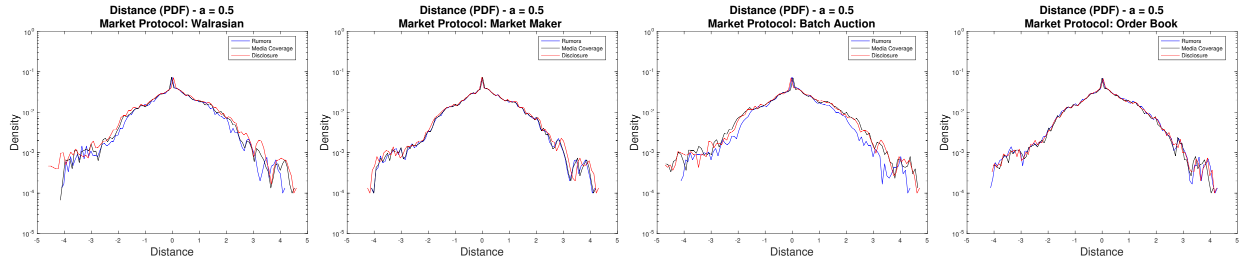

Figure 24: Distribution of Distance (Equation 14) with autocorrelation $a = 0.5$. Market protocols: Walrasian (First Panel from the left), Market Maker (Second Panel), Batch Auction (Third Panel), Order Book (Right Panel).

Generally speaking, results for market pricing quality (Figures 21 and 22) are robust across various market trading mechanisms. Concerning market informational efficiency (Figure 21), no market mechanism provides alignment of market pricing with fundamental information through time in all circumstances, although market sentiment is neutral in all cases. Relative to the baseline, order book and batch auction tend to worsen the market pricing quality. Only the Walrasian auction improves it when information is largely diffused and the market confidence α is neutral (that is, $\alpha = 0.5$) for all investors.

Relative returns difference (Figure 22) is sensitive to various market mechanisms. In particular, the batch auction market mechanism tends to worsen the market systemic performance, while the order book and the market maker mechanisms improve it relative to the baseline.

Results for market exuberance (Figures 23 and 24) are robust across various market trading mechanisms. In particular, all market mechanisms provide similar systemic performances for distance: the relative distance between the realized market price and the fundamental signal of reference only depends on heterogeneous individual expectations and not from the mechanism that generate the price. Concerning added noise, order book and batch auction worsen the market pricing quality, while the Walrasian auction improves it under the disclosure regime (where information is largely diffused) and the market confidence α is neutral (that is, $\alpha = 0.5$) for all investors.

These robust provide a strong corroboration of the results provided in the main text that remain valid under very different market mechanisms.

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. Our finding also proved to be robust across various market trading mechanisms. Only the Walrasian auction, which concentrates orders and treats them simultaneously, significantly improves the market pricing quality under the disclosure regime when market confidence is neutral for all investors.

We show that only when all the investors are fully informed and their market confidence is neutral, the market clearing pricing delivers an efficient market price. By relaxing these quite heroic assumptions, the market pricing process shows material and persistent divergence from the fundamental signal of reference, while market volatility is increased by the presence of news. Fat tails in volatility distribution are also exacerbated by speculative attitudes among investors, pointing to the possibility of extreme events in those cases.

Our market dynamics shows endogenous generation of illiquidity when speculative attitudes dominate investor behavior. In particular, market satisfaction of orders is improved under the media scenario where the news is diffused to around half of the population. This generate a large amount of arbitrage opportunities, that disappear when most investors are informed. Our result implies that market satisfaction depends strongly from the interaction between investor heterogeneity and information diffusion.

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. Conservative attitudes improve on this latter alignment under all information diffusion scenarios, while the disclosure regime does not fundamental reshape its distribution function. On the contrary, speculative attitudes worsen the alignment, since they facilitate a persistent disconnection between the fundamental performance and the investor expectations through time.

In conclusion, contrary to the fully efficient market hypothesis, these findings imply that market pricing does not deliver a good estimate of the fundamental performance over time and circumstances. Therefore, fundamental information generation and provision plays an active and specific role in the market pricing process, while the market price series alone is not sufficient to inform investor expectations and trade decisions.

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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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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.

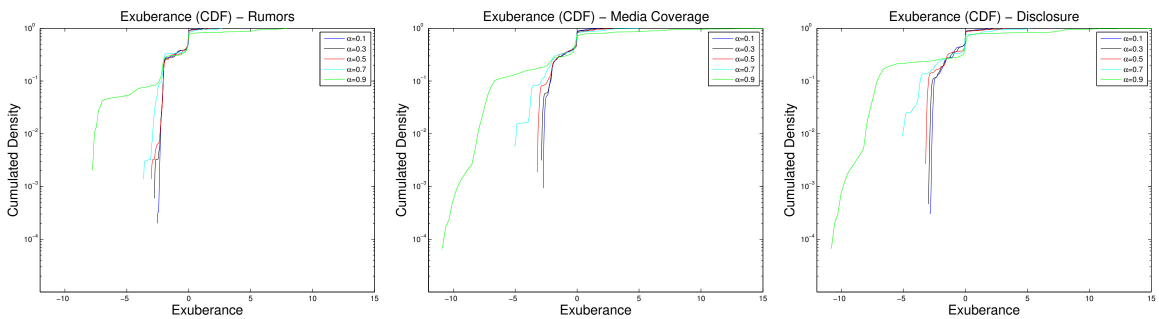

Figure 1: Exuberance defined according to Equation 6: $p_t^w - p_t - NN_t$. Distributions are computed for 100 simulations, each providing data for 300 time periods.

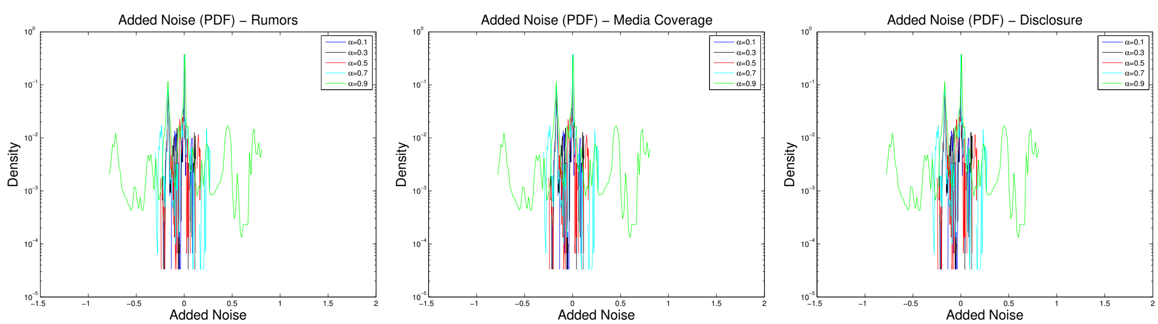

Figure 2: PDF of Added Noise (Equation 12 in the main text). Distributions are computed from values from 100 simulations, using data from each of their 300 time periods.

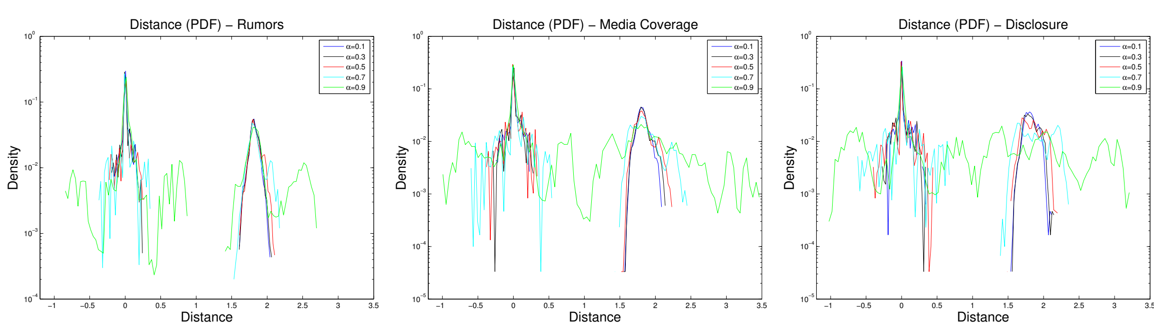

Figure 3: PDF of the Distance (Equation 14 in the main text). Distributions are computed from values from 100 simulations, using data from each of the 300 time periods.

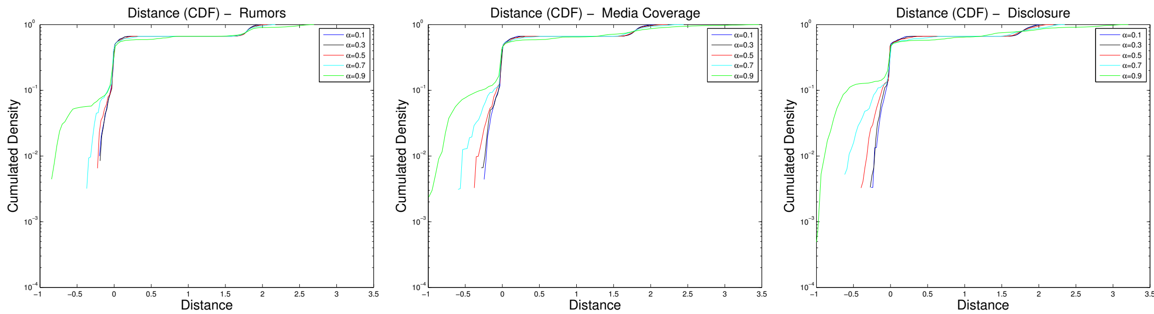

Figure 4: CDF of the Distance (Equation 14). Distributions are computed from values from 100 simulations, using data from each of the 300 time periods.

2 Additional Figures for the Auto-correlated case

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

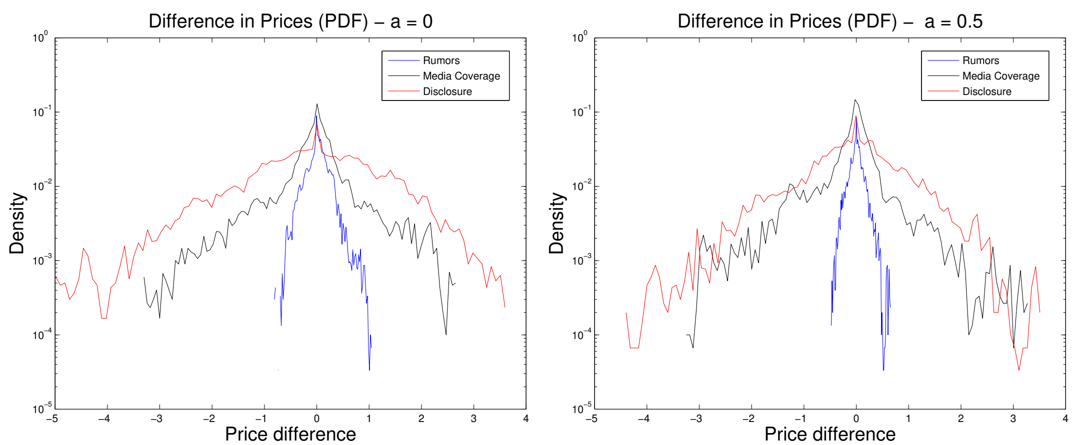

Figure 5: PDF of the Difference in prices $p_t^w - p_t$ (between with and without shock, on each single data) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$.

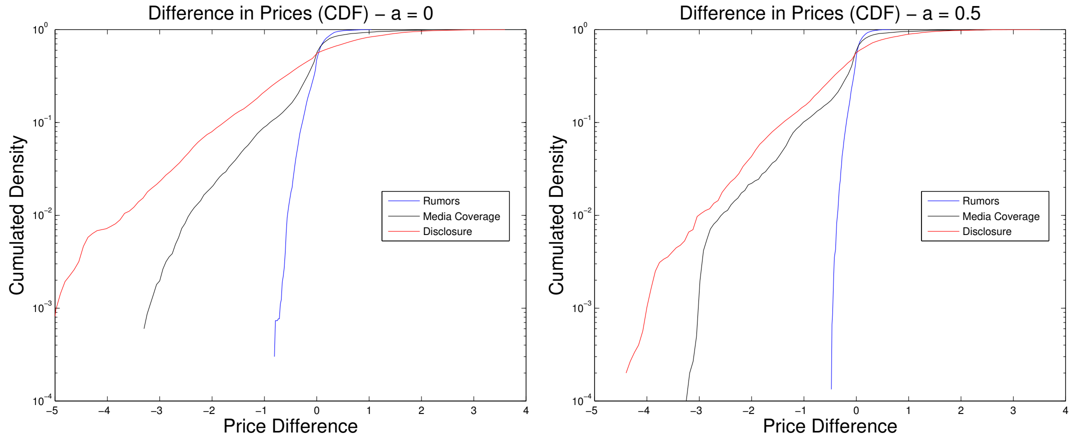

Figure 6: CDF of the Difference in prices $p_t^w - p_t$ (between with and without shock, on each single data) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$

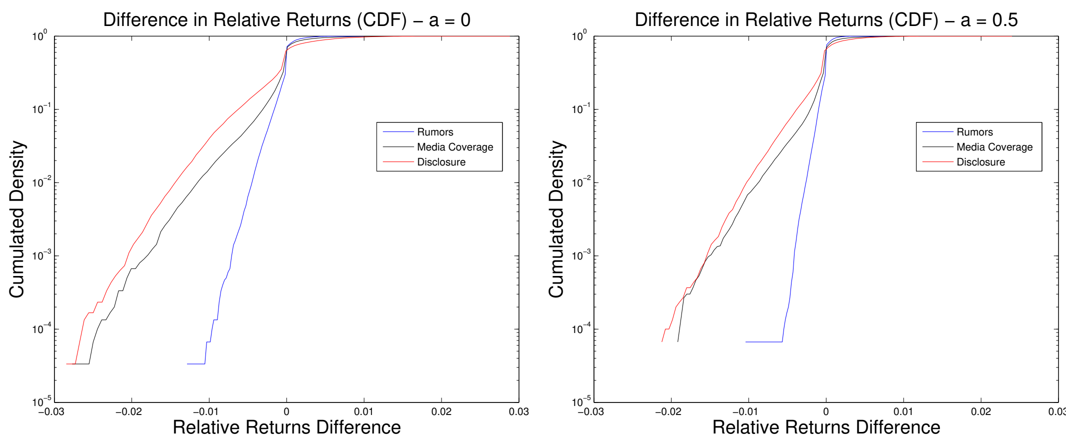

Figure 7: CDF of Difference in Relative Returns in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Relative returns are compute respectively as: $Returns_t^w = \frac{p_t^w - p_{t-1}^w}{p_{t-1}^w}$ 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 $a = 0.5$.

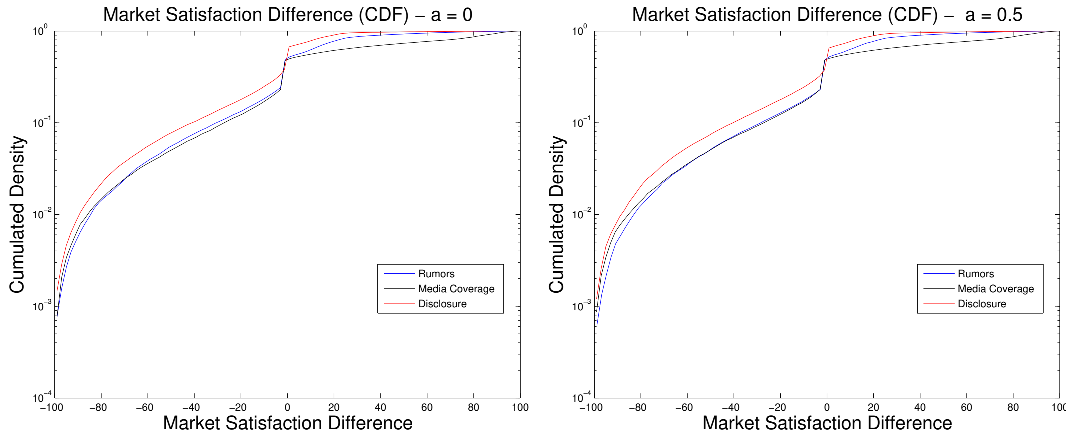

Figure 8: CDF of Difference Market Satisfaction (between the cases with and without shock), as defined in Equation 9 in the main text. Distributions are computed from 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$.

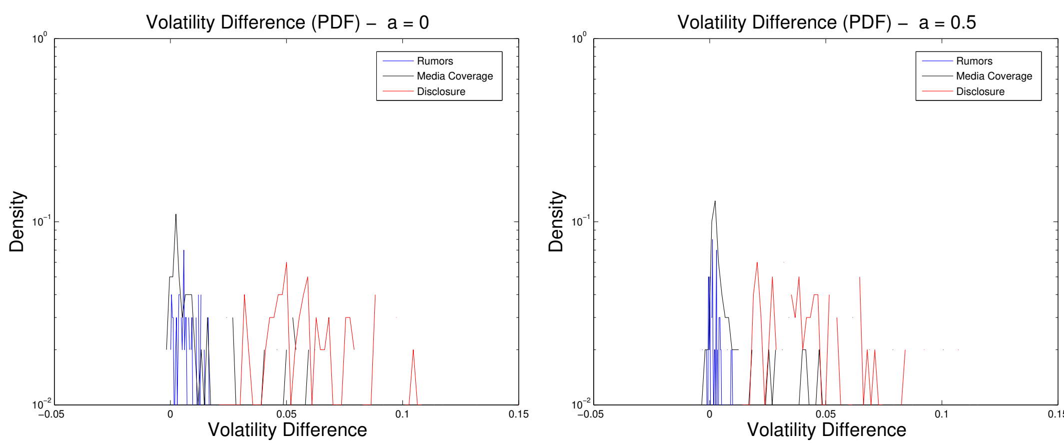

Figure 9: PDF of Market Volatility between the cases with and without shock defined respectively as $\frac{Std(p_t^w)}{mean(p_t^w)}$ and $\frac{Std(p_t)}{mean(p_t)}$. Distributions are computed from 100 simulations (for each combination of auto-correlation of shocks and degree of information). One value for each simulation. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$.

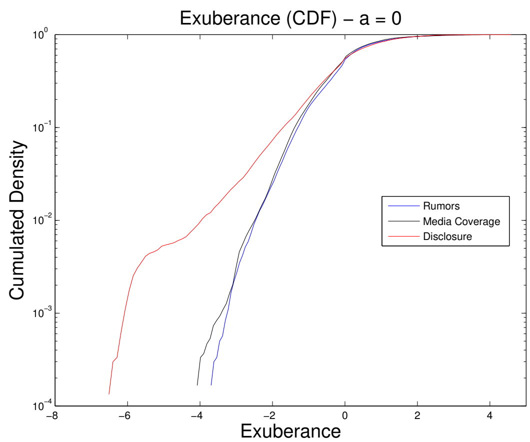

Figure 10: CDF of Exuberance in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Each Figure is a different level of autocorrelation. Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$. Exuberance is computed according to Equation 10 in the main text.

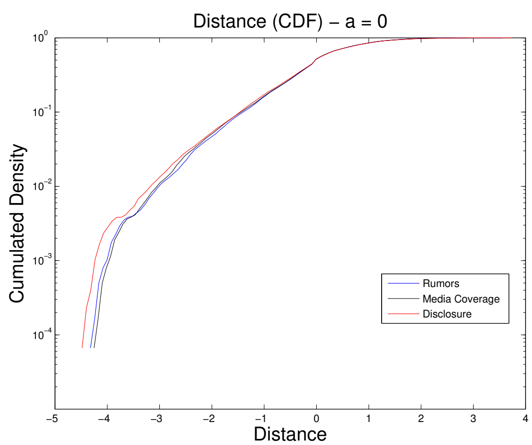

Figure 11: CDF of Distance in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Each Figure is a different level of autocorrelation. Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$. Distance is computed according to Equation 14 in the main text.

3 Description of additional market protocols

We hereby describe the technical details of the alternative trading protocols we use to corroborate our analysis.

3.1 Walrasian Auction

The Walrasian auction mechanism assumes that, at every market period t, the market protocol generates a clearing equilibrium with aggregate demand equal to aggregate supply. When the clearing session starts, each agent submits its demand/supply order according to its focal price. Every agent wishes to buy one share when the auction price is lower than its focal price, and sell one share when it is higher.

For each possible price level, the market mechanism sums up demand orders (positive) in aggregate demand D, and supply orders (negative) in aggregate supply S. The market clearing price is then determined by setting the price p^* that satisfies clearing condition $D = S$.

For sake of simplicity, our agents are in even number and wish to exchange one share at each period. Therefore, the market clearing price that satisfies the previous condition is equal to the median price among all the focal prices included in submitted orders.

3.2 Market Maker

Under the market maker mechanism, the market maker is a special agency that calls a market price p_{t+1} before trade starts. This agency operates in view to enhance market liquidity, seeking for market order satisfaction. At the beginning of time, by assumption, the agency calls the initial market price $p_{t=0} = 10$.

Observing p_t, the agents compute their desired demand/supply positions. Since the current price can now be used in forecasting, their focal price $E_{i,t}(p_{t+1})$ is computed on $p_t - p_{t-1}$ according to the condition : $p_t = E(F_t|I_t)I_t = \epsilon_t$ with ϵ_t i.i.d. $\rightarrow p_t \sim N(F_{mean}, \epsilon_{var})$, reported in the main text.

The difference between the focal price and the called price determines the agents' position. If the called price is lower than the focal price, the agent i would buy one share (D_i) from the market maker. If the called price is higher than the focal price, the agent i would sell one share (S_i) to the market maker. All the orders are settled with the market maker, which keeps its own inventory. As under the Walrasian auction, the demands/supplies of all agents are satisfied at the end of the trade session. By assumption, no outside supply of shares exists. The inventory of the market maker after each trading session t is then updated by the opposite amount of the aggregate change in all the agents' possession.

Before the next market session, at $t + 1$, the market maker updates its called price p_{t+1}.

If its share inventory is decreasing (that is, demand exceeded offer in the previous trade session), the market maker increases the called price to induce more agents to sell some of their holdings. Vice-versa, the market maker decreases the called price to induce agents to buy some shares. We assume the following linear price update rule:

$$p_{t+1} = b \cdot \text{median}\left(E_{i,t}(p_t)\right) + (1-b) \cdot p_t$$

Where $b = \frac{|(\sum D - \sum S)|}{N}$. Indeed the market maker pricing update provides liquidity moving the price in the direction of countering excess demand or supply. The convergence is not instantaneous and depends on the size of this excess relative to the maximum amount of shares that can be traded. The latter amount is equal to the population N by construction (since each agent can trade one share at the time). This formulation is in line with LeBaron et al. (2001) and the Walrasian clearing price (comp. with Anufriev and Panchenko 2009, Equation 13).

3.3 Batch auction

Under the batch auction mechanism, agent i uses simple strategic considerations to determine its belief on the clearing market price p_{t+1}. Namely, the agent extracts its belief as a random draw from a normal distribution with mean p_t and standard deviation σ (fixed at $\sigma = 0.02$ for simulation calibration). The realisations are independent over time and across agents. This implies that an agent believes that it is likely that the next market price p_{t+1} is close to the last closing price p_t.

The agent compares its random draw to its focal price $E_{i,t}(p_t+1)$ and decides its position. Every agent would wish to buy one share when its price belief is lower than its focal price, and sell one share when it is higher. On this basis, it submits an order for buying or selling one share at its focal price[1].

All orders are submitted simultaneously and ranked on both sides of the market. On the demand side, the price sequence is decreasing. On the supply side, the price sequence is increasing. This procedure defines two one-share-step-level, aggregate market curves. The clearing price is then determined at the intersection point of these curves, or the average of the lowest and highest clearing prices if the intersection is an interval rather than a point.

[1] A robustness check has been conducted where orders are submitted at price belief amounts instead than at focal prices. Results are analogous and available upon request to the authors.

In those cases when demand and supply do not intersect, the clearing price p_{t+1} is set at the median of order prices[2].

Orders are satisfied at this price p_{t+1} between those agents who submitted bids (asks) no lower (no higher) than p_{t+1}. Other agents do not trade. The session volume is the total traded number of shares.

3.4 Order book

In the order book market mechanism, each agent will place only one buy or sell order during the session. Agents send orders one after another. The sequence in which agents place orders is determined randomly and varies across market sessions.

Individual market orders are established in the same way as for the batch auction mechanism [3]. There is an electronic order book containing unsatisfied orders placed during the current trading session. At the end of each session, all unsatisfied orders are removed from the book.

When a new buy or sell order arrives, it is checked against the counter-side of the book. The order is then executed if it finds a match, i.e., a counter-side order at requested or better price, starting from the best available price on the counter side (the lowest offer price / the highest demand price). If bid and ask cross (bid is above ask), transaction is executed at the price equal to the bid or ask that came first. An unsatisfied order remains queuing in the book. Matched transactions are then executed at various prices during the session. However, agents do not update their focal price expectation throughout the market session.

The market clearing price for the next session is fixed at the matching price established through the last matched transaction. It may significantly depend on the sequence in which transactions are executed. Since several prices are formed within each session, we use the mean session price as reference for simulation analysis. If no transactions occur, the clearing price p_{t+1} is set at the median of expressed order prices on both sides of the market[4]. The session volume is the total traded number of shares.

[2] Overall 2.7% of prices were generated through this market mechanism.

[3] Orders are placed at focal prices $E_{i,t}(p_t)$. A robustness check was conducted where orders are submitted at price belief amounts instead than at focal prices. Results are analogous and available upon request to the authors.

[4] Overall 0.33% of prices were generated through this market mechanism option.

4 Additional figures for market trading mechanisms

We hereby report additional figures concerning the case of auto-correlated news flow under various market mechanisms (see Section 5 of the main text for the main results and the previous section of this Supplementary Material for the description of the market protocols.).

For simulation purpose, 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.

4.1 Market pricing quality under various market mechanisms

This section provides the analysis developed in Sections 4.1.1 and 4.2.1 for the various market mechanism protocols.

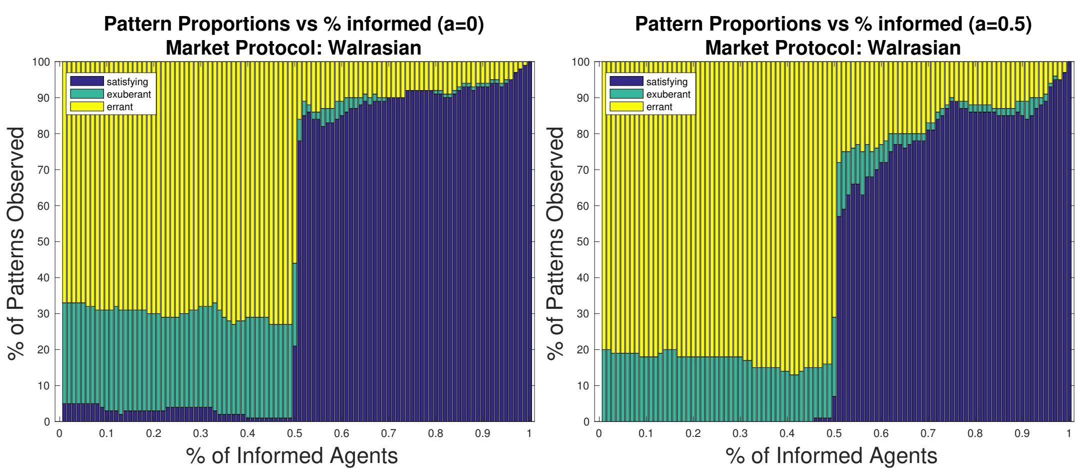

Figure 12: Protocol Walrasian Auction. Left Panel: no auto-correlation ($a = 0$). Right Panel: auto-correlation ($a = 0.5$)

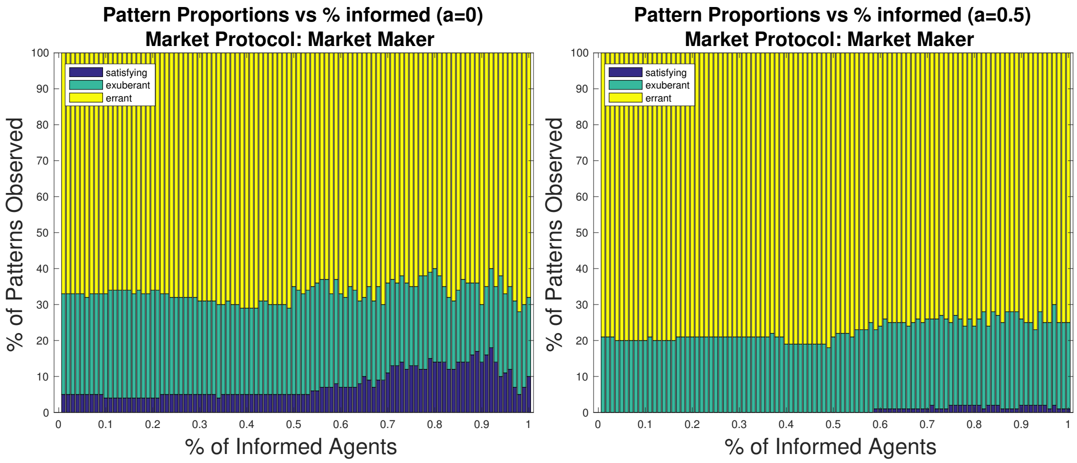

Figure 13: Protocol Market maker. Left Panel: no auto-correlation ($a = 0$). Right Panel: auto-correlation ($a = 0.5$)

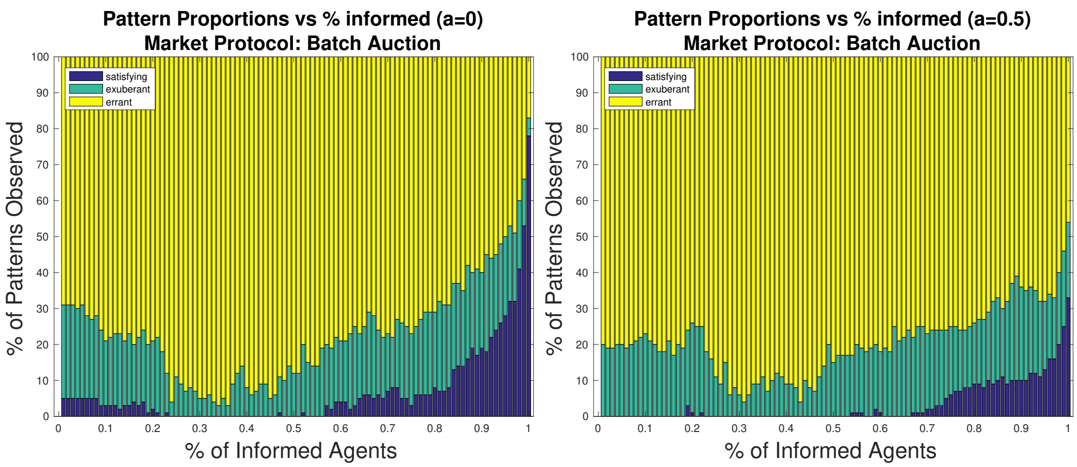

Figure 14: Protocol Batch Auction. Left Panel: no auto-correlation ($a = 0$). Right Panel: auto-correlation ($a = 0.5$)

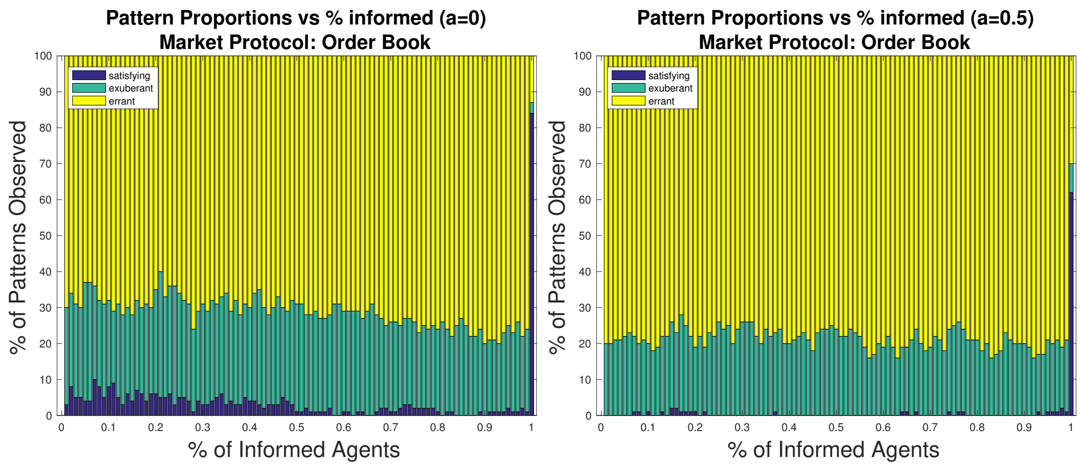

Figure 15: Protocol Order Book. The mean session price is used for computation. Left Panel: no auto-correlation ($a = 0$). Right Panel: auto-correlation ($a = 0.5$)

4.2 Market Protocol: Walrasian auction

We provide descriptive statistical measures for systemic performance under the Walrasian auction market mechanism.

4.2.1 Distribution of Prices and Returns

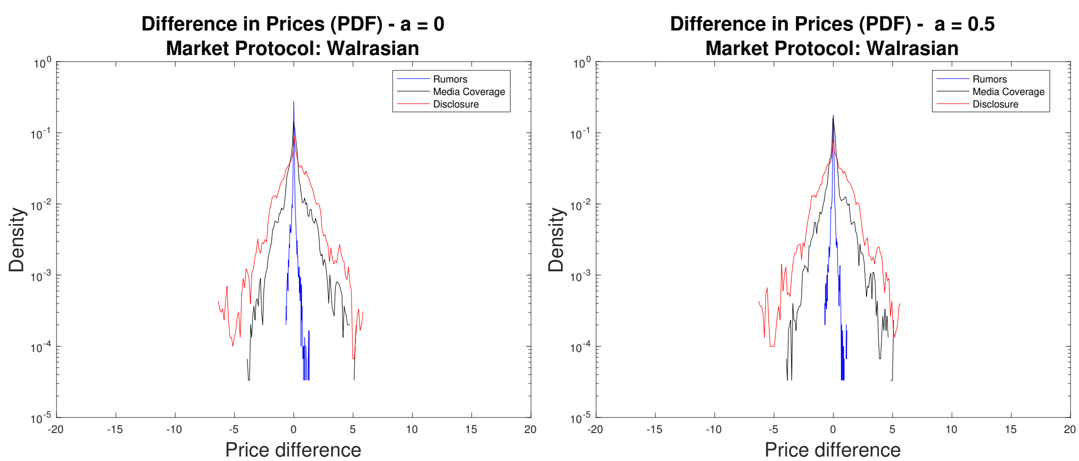

Figure 16: Market Protocol: Walrasian Auction. PDF of the Difference in prices $p_t^w - p_t$ (between with and without shock, on each single data) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time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

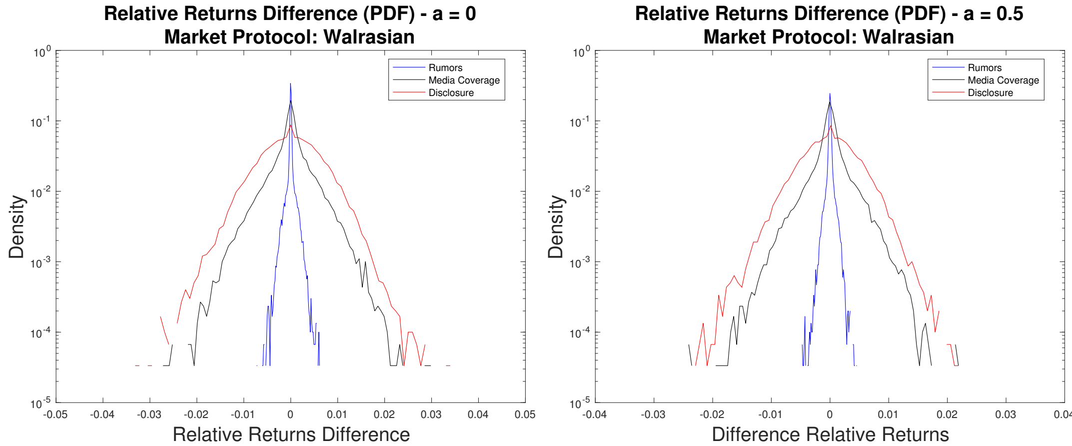

Figure 17: Market Protocol: Walrasian Auction.PDF of Difference in Relative Returns (between with and without shock, on each single data) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Relative returns are compute respectively as: $Returns_t^w = \frac{p_t^w - p_{t-1}^w}{p_{t-1}^w}$ 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 $a = 0.5$

4.2.2 Market satisfaction and Volatility

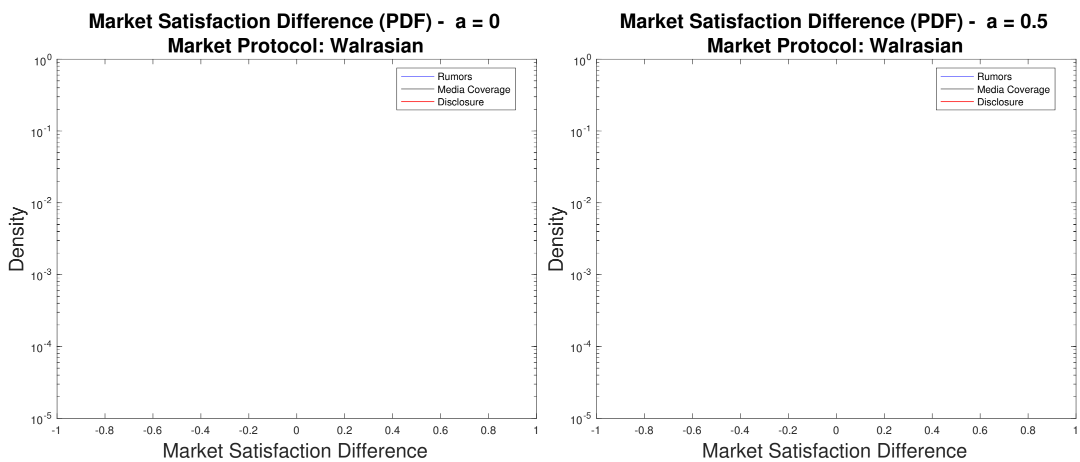

Figure 18: Market Protocol: Walrasian Auction. By construction, market satisfaction as defined by Equation 9 in the main text is always at its maximum value in all cases. Therefore, no difference can occur. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$

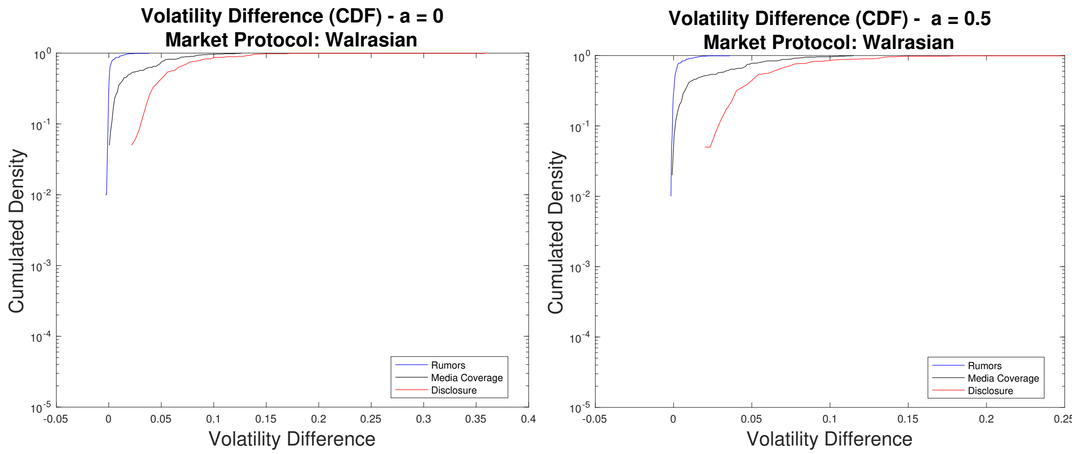

Figure 19: Market Protocol: Walrasian Auction. CDF of Market Volatility between the cases with and without shock defined respectively as $\frac{Std(p_t^w)}{mean(p_t^w)}$ and $\frac{Std(p_t)}{mean(p_t)}$. Distributions are computed from 100 simulations (for each combination of auto-correlation of shocks 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 $a = 0.5$.

4.2.3 Market informational efficiency - Distributions

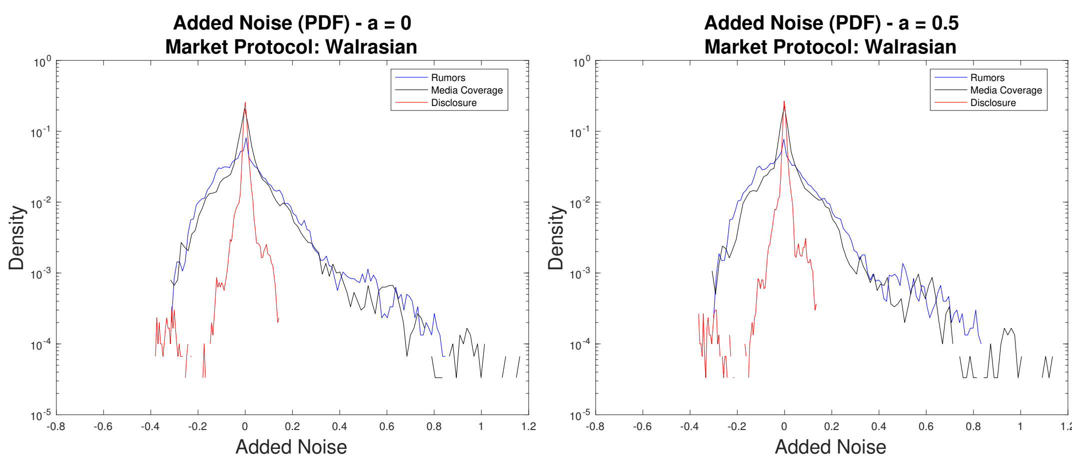

Figure 20: Market Protocol: Walrasian Auction. Added noise (Eq. 12) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$

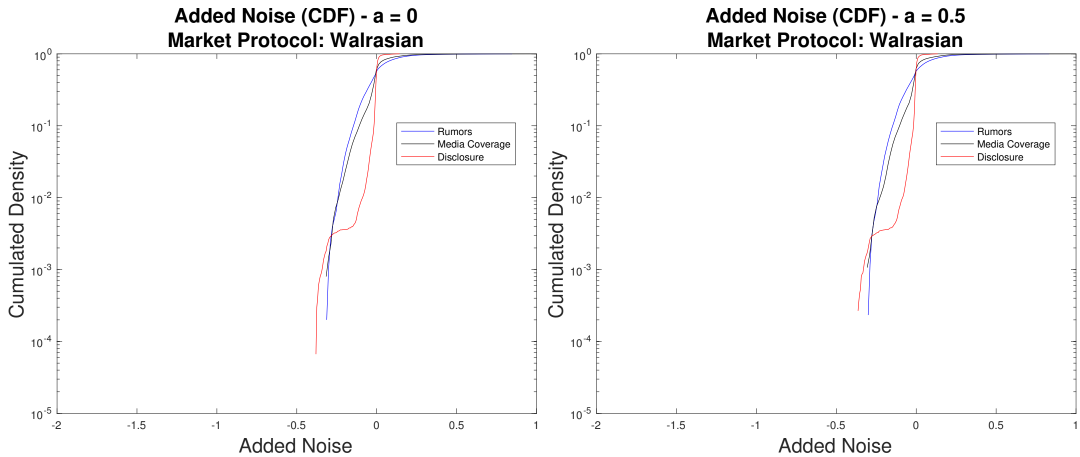

Figure 21: Market Protocol: Walrasian Auction. CDF of Added Noise (Eq. 12) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$

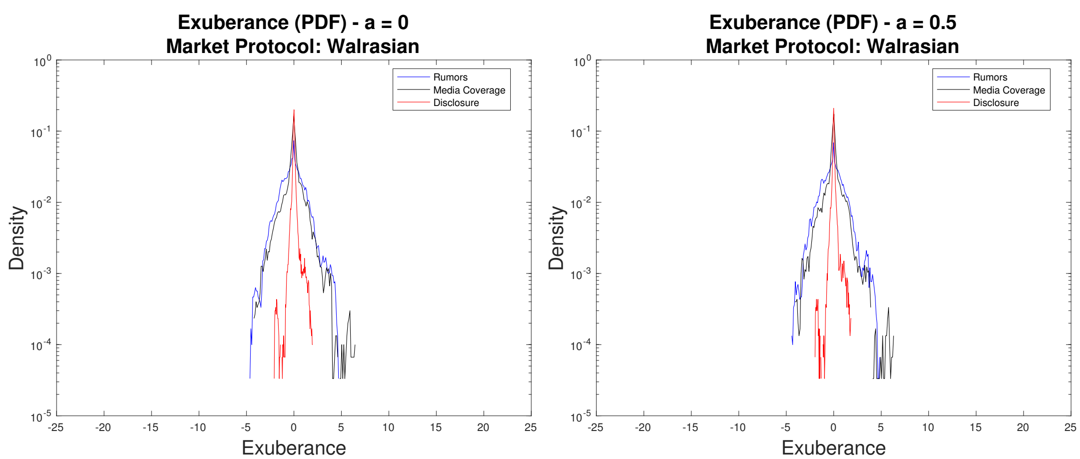

Figure 22: Market Protocol: Walrasian Auction. PDF of Exuberance in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Each Figure is a different level of autocorrelation. Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$. Exuberance is computed according to Equation 10 in the main text.

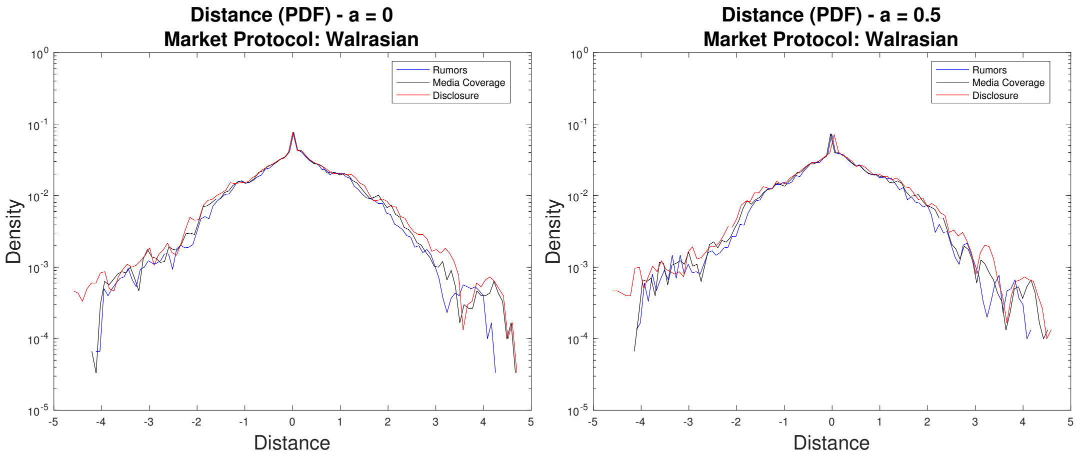

Figure 23: Market Protocol: Walrasian Auction. PDF of Distance (Equation 14) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Each Figure is a different level of autocorrelation. Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$. Distance is computed according to Equation 20 in the main text.

4.3 Market Protocol: Market Maker

We provide descriptive statistical measures for systemic performance under the market maker protocol.

4.3.1 Distribution of Prices and Returns

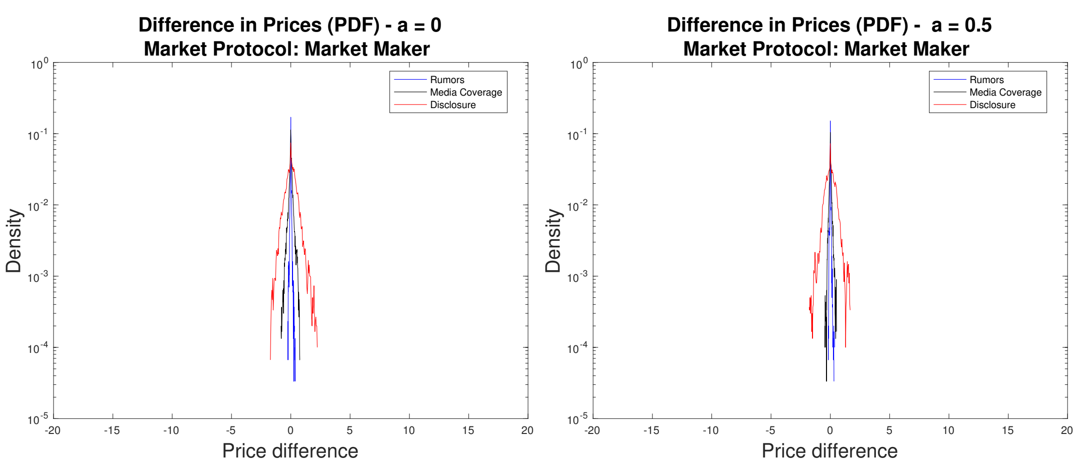

Figure 24: Market Protocol: Market Maker. PDF of the Difference in prices $p_t^w - p_t$ (between with and without shock, on each single data) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$.

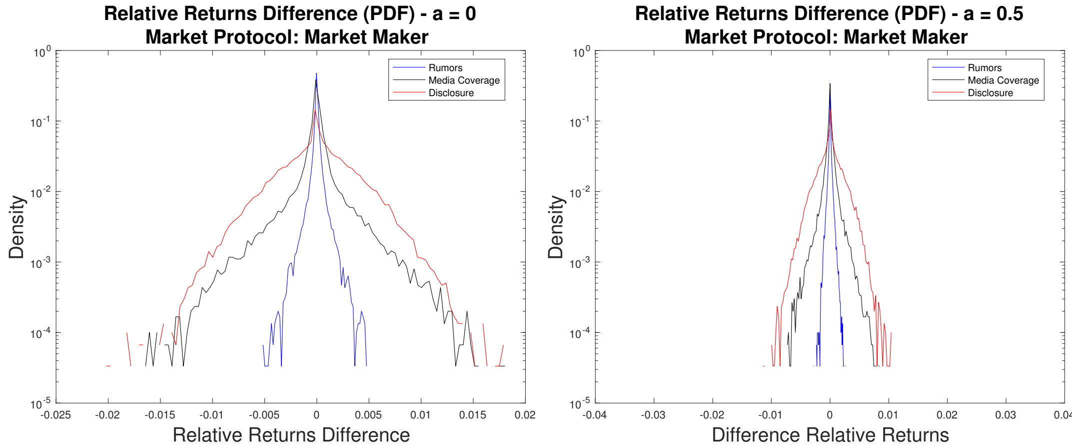

Figure 25: Market Protocol: Market Maker.PDF of Difference in Relative Returns (between with and without shock, on each single data) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Relative returns are compute respectively as: $Returns_t^w = \frac{p_t^w - p_{t-1}^w}{p_{t-1}^w}$ 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 $a = 0.5$

4.3.2 Market satisfaction and Volatility

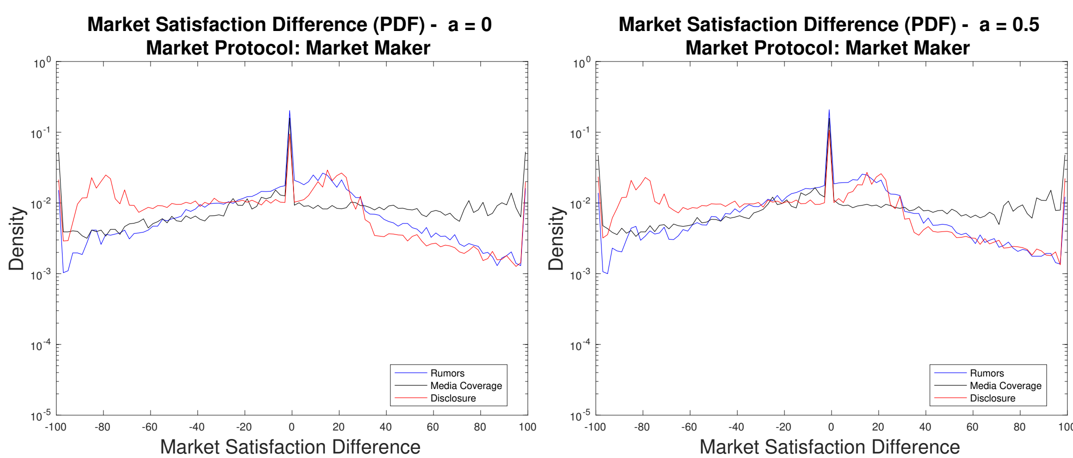

Figure 26: Market Protocol: Market Maker. PDF of Difference in Market Satisfaction (between the cases with and without shock), as defined in Equation 9 (main text). Distributions are computed from 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions 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 $a = 0.5$

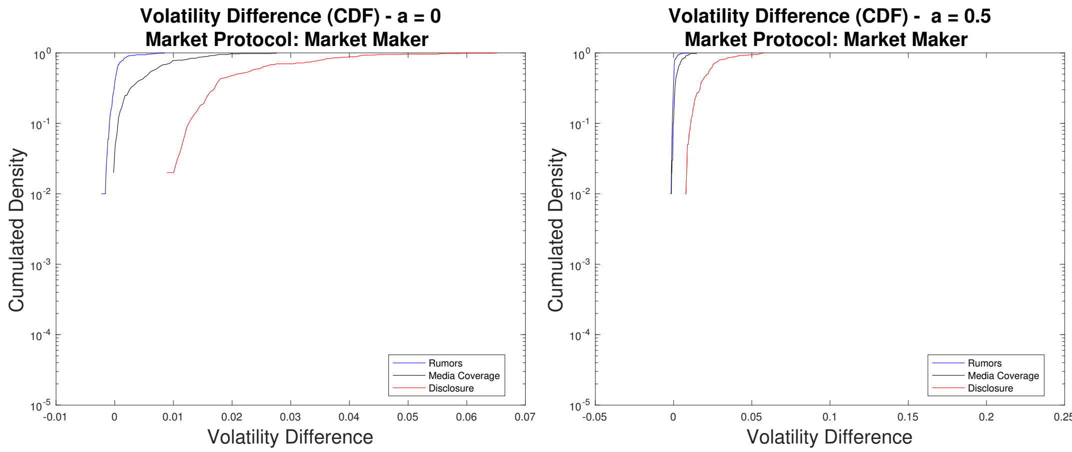

Figure 27: Market Protocol: Market Maker. CDF of Market Volatility between the cases with and without shock defined respectively as $\frac{Std(p_t^w)}{mean(p_t^w)}$ and $\frac{Std(p_t)}{mean(p_t)}$. Distributions are computed from 100 simulations (for each combination of auto-correlation of shocks and 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 $a = 0.5$.

4.3.3 Market informational efficiency - Distributions

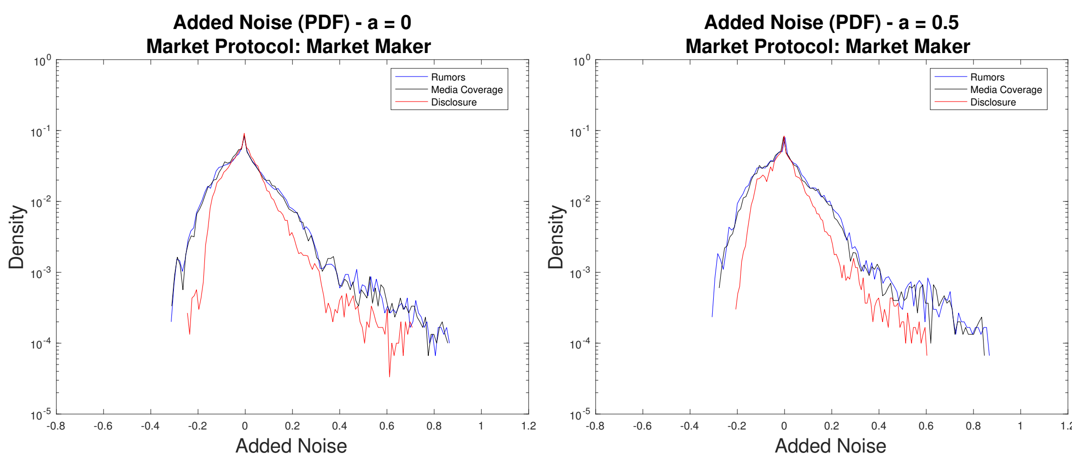

Figure 28: Market Protocol: Market Maker. Added noise (Eq. 12) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$

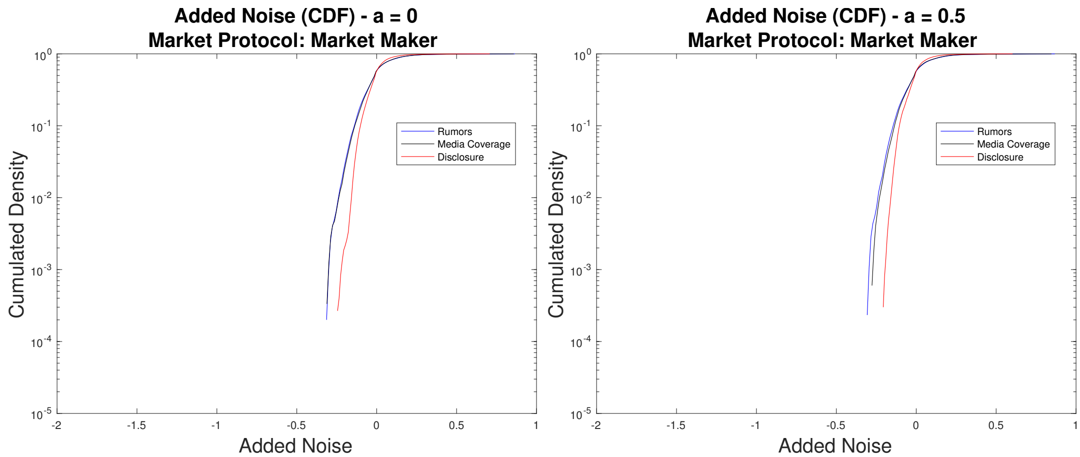

Figure 29: Market Protocol: Market Maker. CDF of Added Noise (Eq. 12) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$

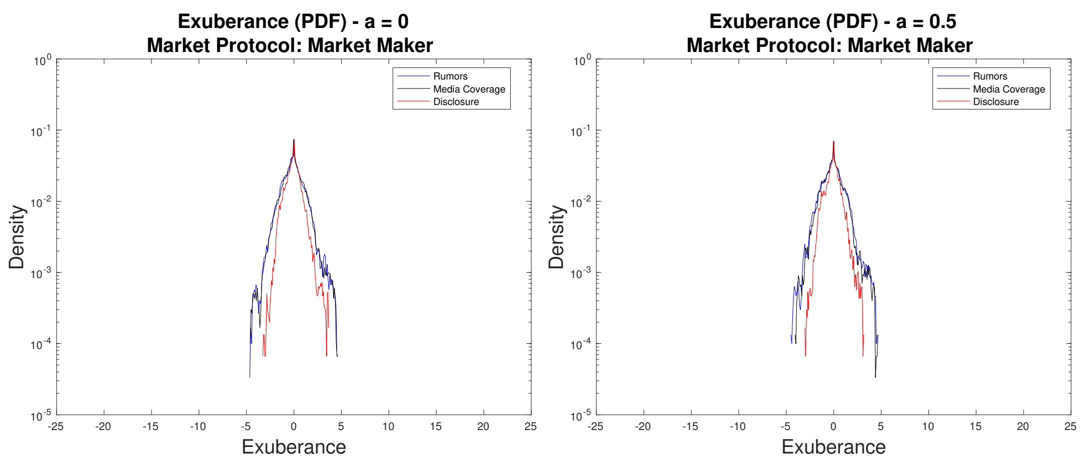

Figure 30: Market Protocol: Market Maker. PDF of Exuberance in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Each Figure is a different level of autocorrelation. Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$. Exuberance is computed according to Equation 10 in the main text.

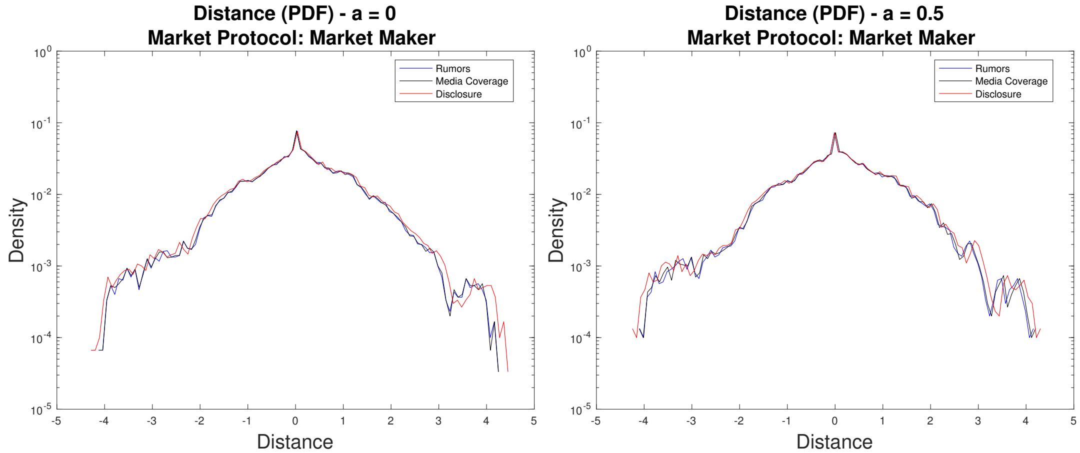

Figure 31: Market Protocol: Market Maker. PDF of Distance (Equation 14 in the main text) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Each Figure is a different level of autocorrelation. Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$. Distance is computed as: $Distance = \frac{p_t^w - FN_{t-1}}{FN_{t-1}}$.

4.4 Market Protocol: Batch Auction

We provide descriptive statistical measures for systemic performance under the batch auction protocol.

4.4.1 Distribution of Prices and Returns

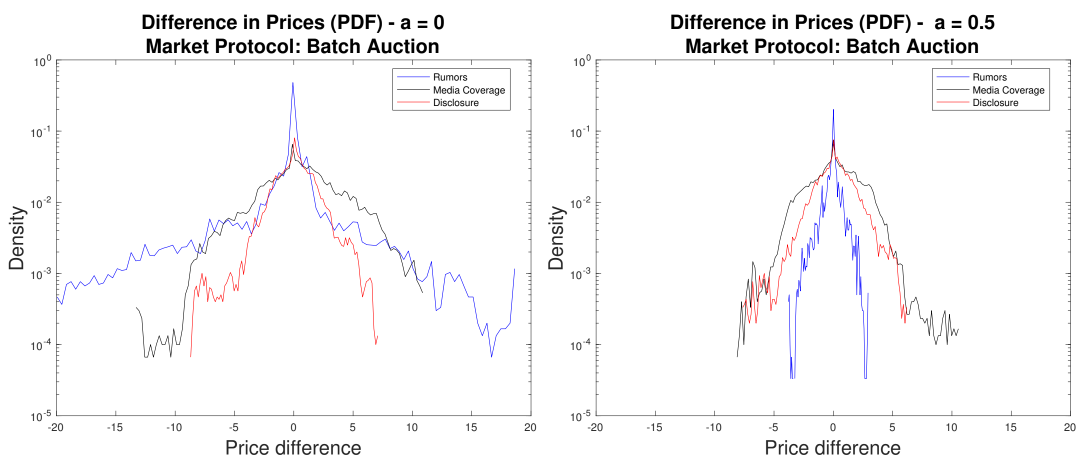

Figure 32: Market Protocol: Batch Auction. PDF of the Difference in prices $p_t^w - p_t$ (between with and without shock, on each single data) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$.

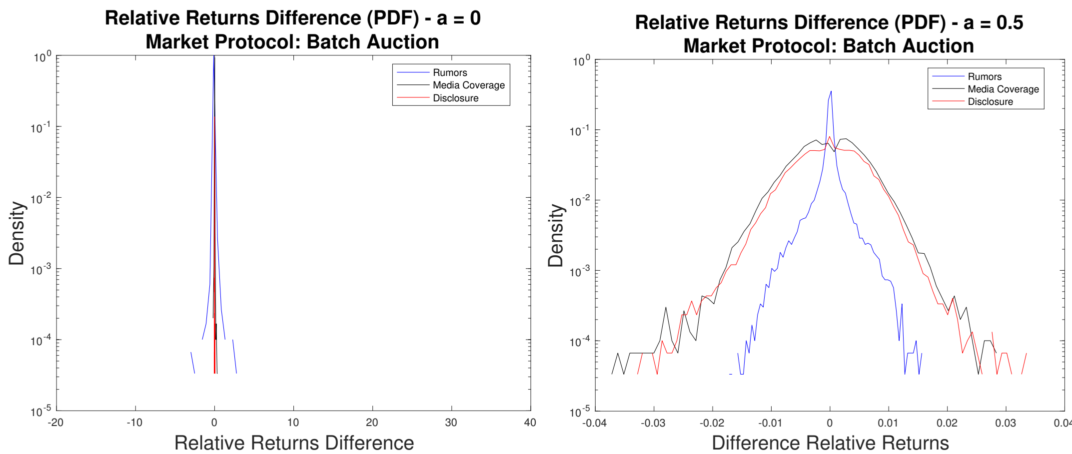

Figure 33: Market Protocol: Batch Auction.PDF of Difference in Relative Returns (between with and without shock, on each single data) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Relative returns are compute respectively as: $Returns_t^w = \frac{p_t^w - p_{t-1}^w}{p_{t-1}^w}$ 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 $a = 0.5$

4.4.2 Market satisfaction and Volatility

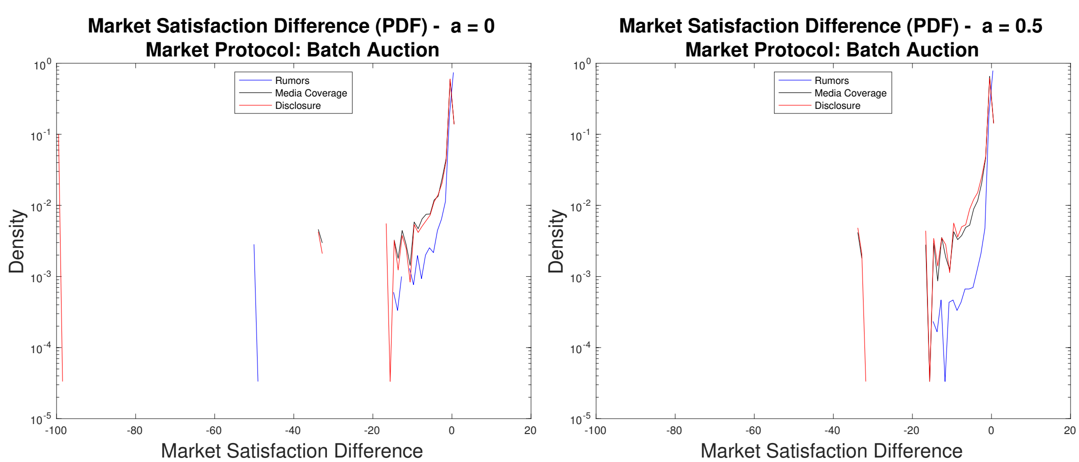

Figure 34: Market Protocol: Batch Auction. PDF of difference in Market Satisfaction (between the cases with and without shock), as defined by Equation 9 in the main text. Distributions are computed from 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions 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 $a = 0.5$.

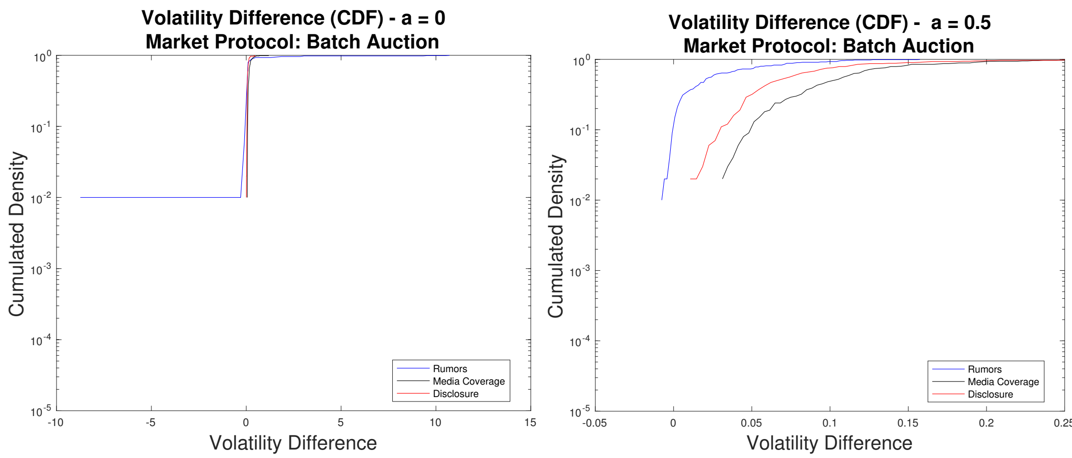

Figure 35: Market Protocol: Batch Auction. CDF of Market Volatility between the cases with and without shock defined respectively as $\frac{Std(p_t^w)}{mean(p_t^w)}$ and $\frac{Std(p_t)}{mean(p_t)}$. Distributions are computed from 100 simulations (for each combination of auto-correlation of shocks and 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 $a = 0.5$.

4.4.3 Market informational efficiency - Distributions

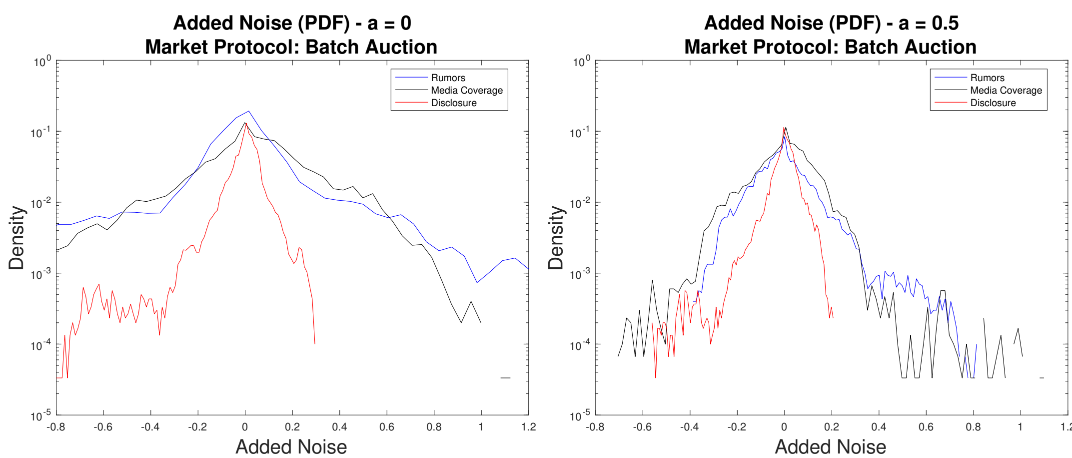

Figure 36: Market Protocol: Batch Auction. Added noise (Eq. 12) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$

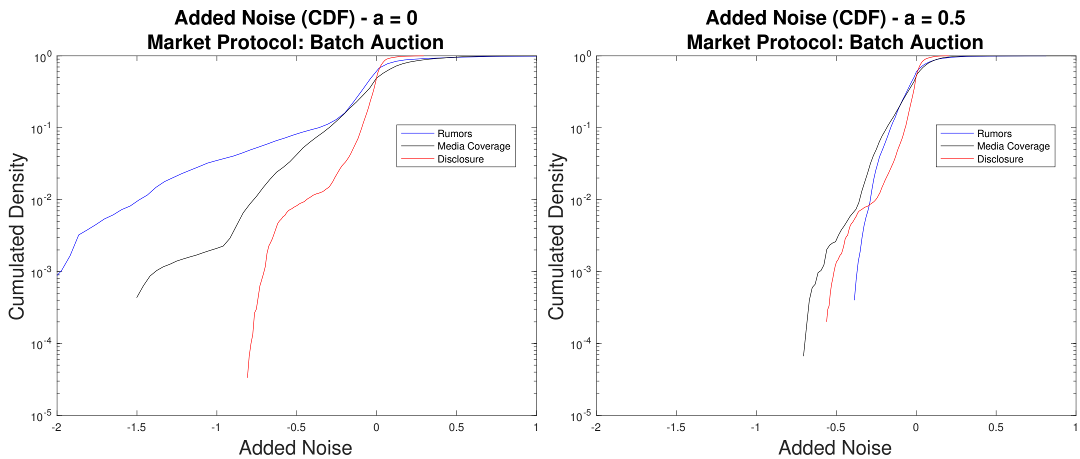

Figure 37: Market Protocol: Batch Auction. CDF of Added Noise (Eq. 12) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$

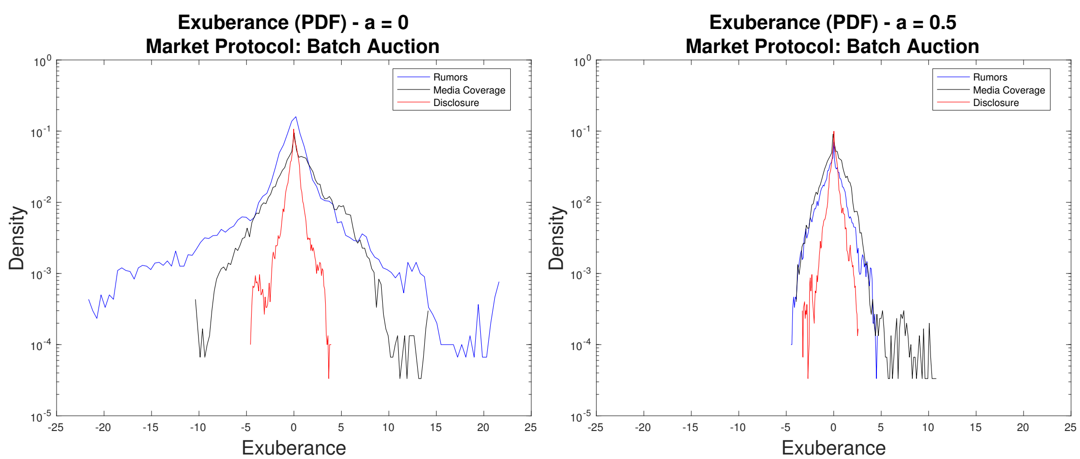

Figure 38: Market Protocol: Batch Auction. PDF of Exuberance in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Each Figure is a different level of autocorrelation. Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$. Exuberance is computed according to Equation 10 in the main text.

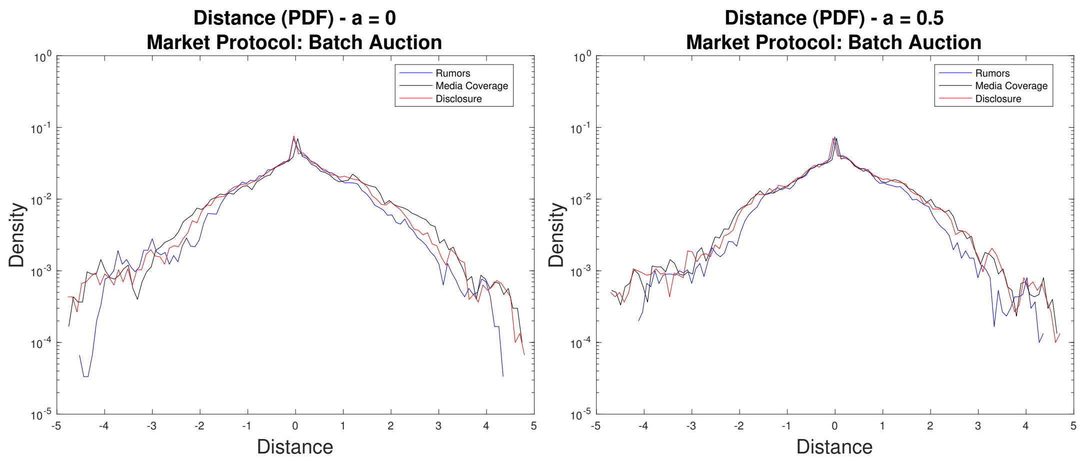

Figure 39: Market Protocol: Batch Auction. PDF of Distance (Equation 14) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Each Figure is a different level of autocorrelation. Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$. Distance is computed as: $Distance = \frac{p_t^w - FN_{t-1}}{FN_{t-1}}$.

4.5 Market Protocol: Order Book

We provide descriptive statistical measures for systemic performance under the order book protocol.

Since several transaction prices may be settled during each session, we use the mean trading session price for simulation analysis for all variables but volatility.

4.5.1 Distribution of Prices and Returns

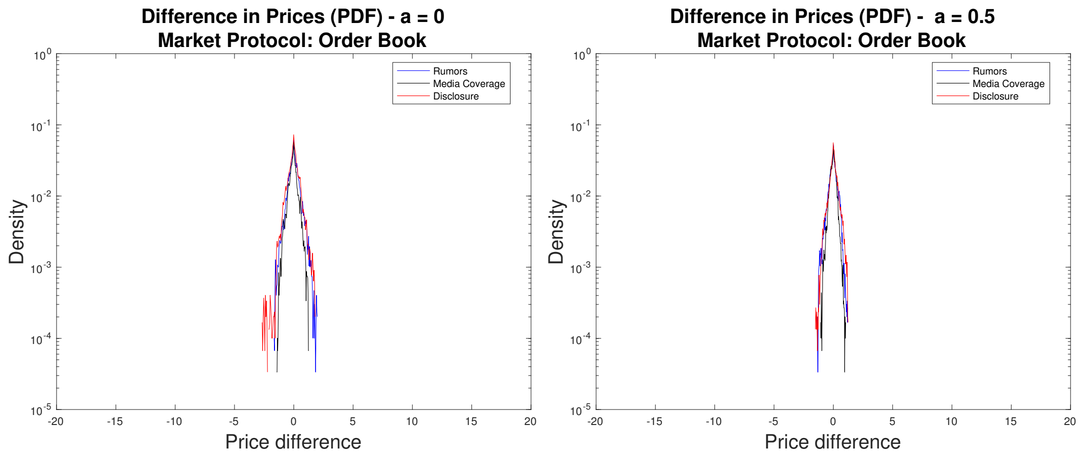

Figure 40: Market Protocol: Order Book. PDF of the Difference in prices $p_t^w - p_t$ (between with and without shock, on each single data) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$.

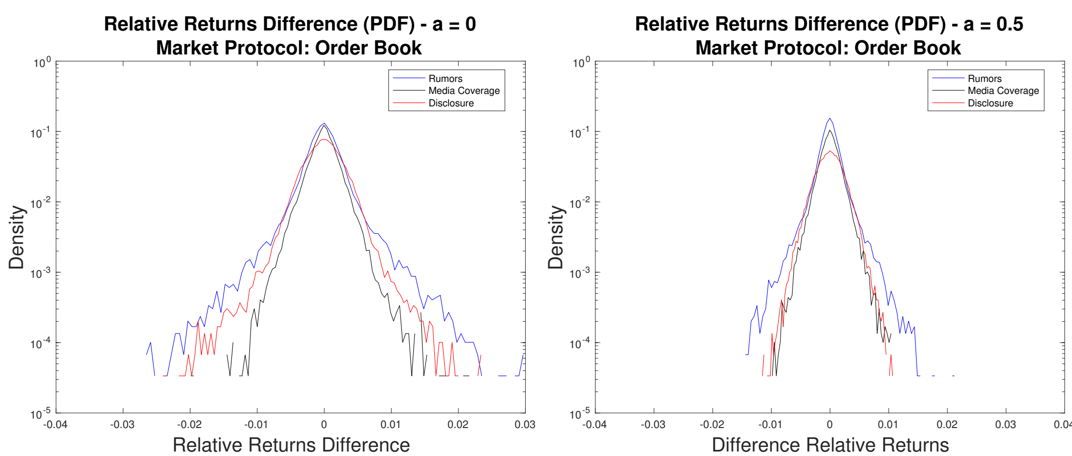

Figure 41: Market Protocol: Order Book. PDF of Difference in Relative Returns (between with and without shock, on each single data) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Relative returns are compute respectively as: $Returns_t^w = \frac{p_t^w - p_{t-1}^w}{p_{t-1}^w}$ 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 $a = 0.5$

4.5.2 Market satisfaction and Volatility

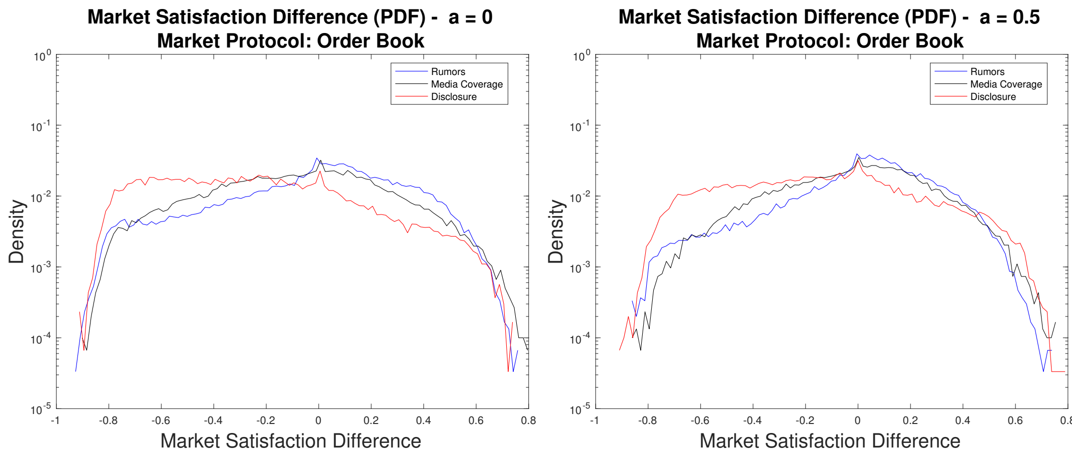

Figure 42: Market Protocol: Order Book. PDF of difference in Market Satisfaction (between the cases with and without shock), as defined by Equation 9 in the main text. In fact, by construction, the market maker satisfies all orders, even when aggregate demand and supply differ. Distributions are computed 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 $a = 0.5$

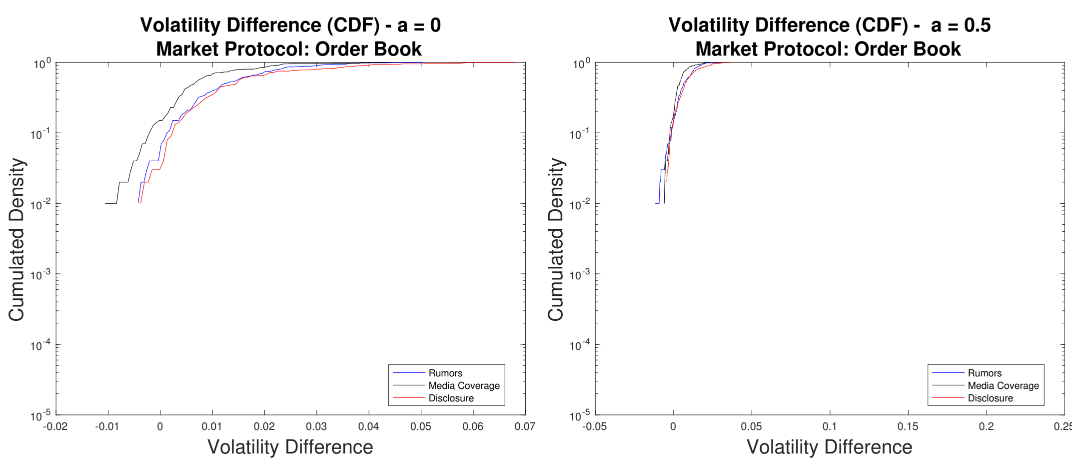

Figure 43: Market Protocol: Order Book. All the settled transaction prices are used for computation. CDF of Market Volatility between the cases with and without shock defined respectively as $\frac{Std(p_t^w)}{mean(p_t^w)}$ and $\frac{Std(p_t)}{mean(p_t)}$. Distributions are computed from 100 simulations (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 $a = 0.5$.

4.5.3 Market informational efficiency - Distributions

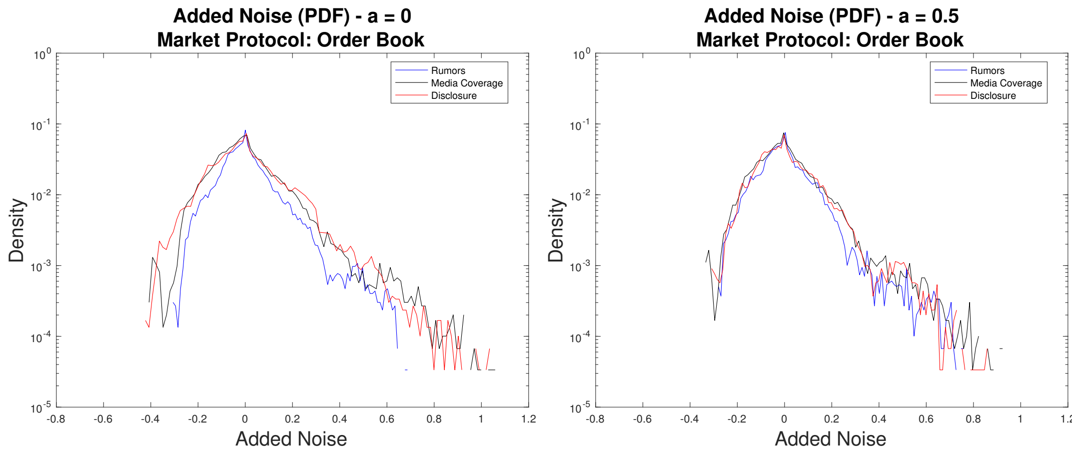

Figure 44: Market Protocol: Order Book. Added noise (Eq. 12) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$

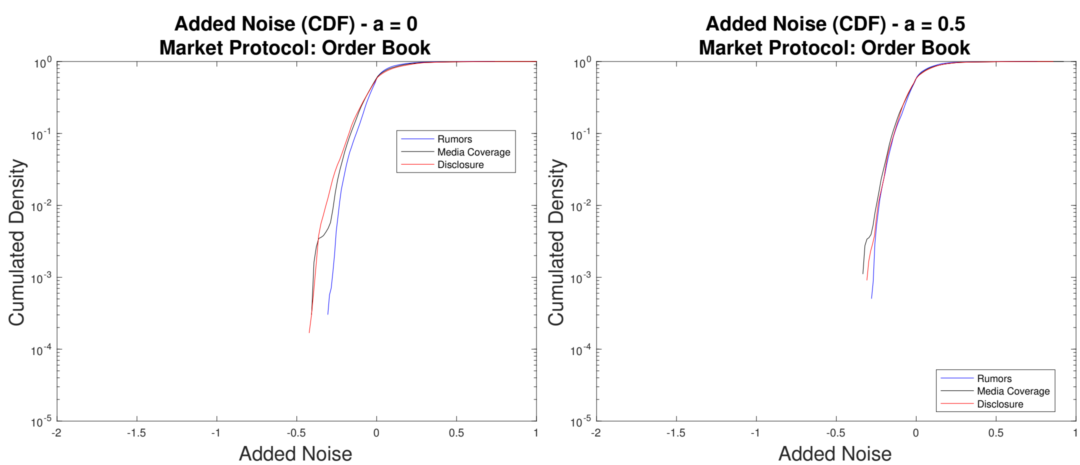

Figure 45: Market Protocol: Order Book. CDF of Added Noise (Eq. 12) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$

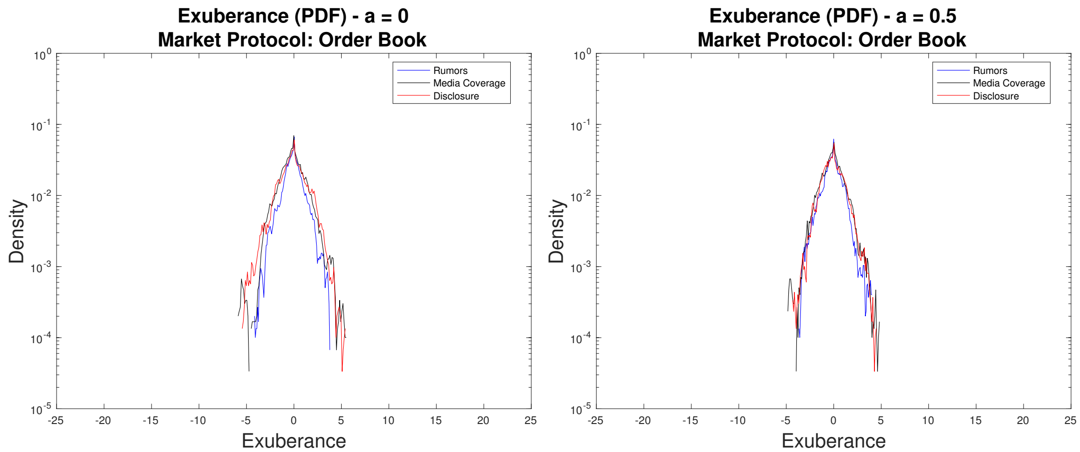

Figure 46: Market Protocol: Order Book. PDF of Exuberance in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Each Figure is a different level of autocorrelation. Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$. Exuberance is computed according to Equation 10 in the main text.

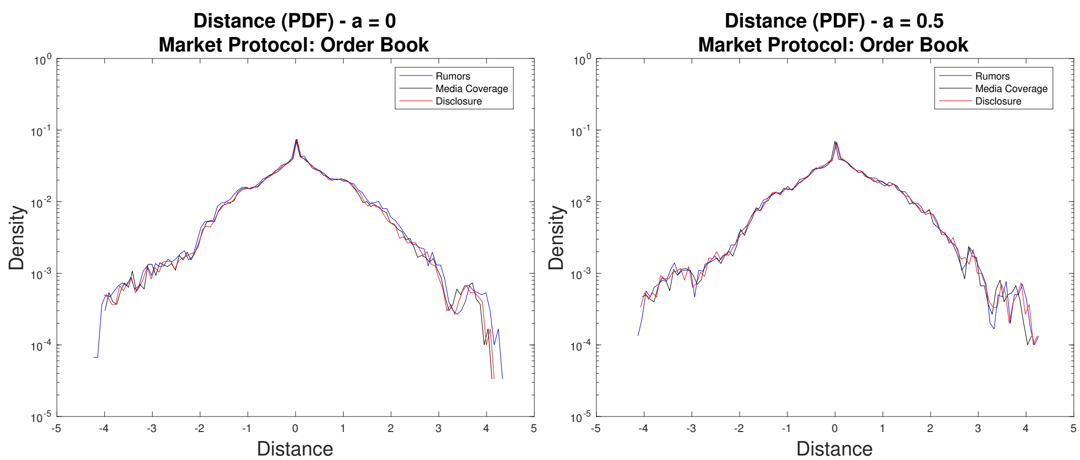

Figure 47: Market Protocol: Order Book. PDF of Distance (Equation 14) in 100 simulations (for each combination of auto-correlation of shocks and degree of information). Each Figure is a different level of autocorrelation. Distributions are computed using data from all 300 time steps. Left Panel corresponds to the case with no auto-correlation. Right Panel corresponds to the case with $a = 0.5$. Distance is computed as: $Distance = \frac{p_t^w - FN_{t-1}}{FN_{t-1}}$.

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