DOES GREATER TRANSPARENCY REDUCE FINANCIAL VOLATILITY?

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Abstract

We develop a model of financial herds and cascades which we first numerically simulate and then empirically test for a panel of 23 OECD and emerging market economies from 2000 to 2009. Financial Cascades, i.e., information free riding behavior, occur when uncertainty is high and markets are informationally opaque. Monte Carlo simulation of the model shows that when traders or investors readily update their "reservation price" and "reservation sell to buy ratio" (points at which they sell or buy), based on new market data, an inverted-U pattern emerges, depicting the effect of market transparency on volatility. In this pattern, increased financial transparency actually increases market volatility at first, only to reduce it later at higher levels of financial transparency. This first (upward) portion seems consistent with the Furman-Stiglitz (1998) thesis that more frequent news and information intensifies volatility, while the second (downward) portion of the inverted-U follows the more conventional wisdom exemplified by the International Monetary Fund's position on lack of transparency as the cause of cascades.

We use two novel measures of financial transparency from World Economics Forum, and find strong support for our model.

Keywords: uncertainty, cascades, transparency, financial volatility, Monte Carlo

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1 Introduction

To state that uncertainty drives stock market volatility is a truism that is experienced everyday by stock market participants around the world but that adds little to the understanding of its underlying reasons. Digging deeper, one may note that the volatility-generating uncertainty may reflect either an underlying lack of financial transparency in an institutional sense, or short-run uncertainties associated with underlying structural or financial crisis. An instance of the latter is fresh from the credit freeze of late 2008 while instances of the former are widely discussed in international policy circles. For example, the 1994-95 Mexican crisis and of the 1997-98 emerging market crisis have been blamed on "a lack of transparency" (IMF, 2001). In this report, lack of transparency is characterized as "inadequate economic data, hidden weaknesses in financial systems, and a lack of clarity about government policies and policy formulation contributed to a loss of confidence that ultimately threatened to undermine global stability." (ibid). Regardless of the source, one might ask; what is the mechanism that links uncertainties (driven by either a lack of transparency or an underlying structural crisis) to stock market volatility? One possible candidate is herd behavior. However, the theoretical work on herd behavior has focused on informational asymmetries, not uncertainty. In this view, herd behavior is a link that connects informational asymmetry to financial cascades and stock market volatility. Thus, Bikhchandani et al. (1992) and Bikhchandani and Sharma (2000) develop a sequential Bayesian updating model where individuals follow others observed behavior regardless of their own private information (definition of herd behavior). Lee (1993) investigated informational cascades in a sequential model in which agents updated their priors upon observing the actions of others and shows that the process is convergent, but fully revealing only if the action set is continuous. This implies a discrete action set as in equity markets (e.g. buy or sell) leaves the possibility of convergence to a non-true state. Moreover, in Lee the observed state is not endogenous, whereas in equity markets, the observe state (price level) is itself a response to the action of the agents (prices fall if most agents short and rise if most agent long). The model in our paper takes the state as endogenous to the action of the agents (more on our contribution below). Chari and Kehoe (2004) on the other hand have preferred to maintain the continuous trading feature, but reproduce herd behavior by endogenizing the timing of investors. In Chari and Kehoe endogenous timing by investors leads to information being trapped, beyond the time point at which a decision to invest (rather than wait for new information) is made. This information trapping mechanism is what leads to herds. (This is a generalization of Lee (1998) in which a fixed cost of trading is introduced which leads investors to stop trading after a point, causing information to be trapped)

Fundamentally, these explanations focus on information asymmetries, but assume that prices themselves accurately reflect fundamentals, that is there is no uncertainly about the price mechanism. But prices may not always accurately reflect fundamentals when as we have seen there is a lack of institutional transparency as has been discussed for example by Gelos and Wei (2002) or in the IMF (2001) report cited earlier. For example, Aggarwal and Wu (2006) show that when markets are less transparent, such as the OTC market in the US, stock market manipulation occurs and during such period volatility is higher. The authors also point to evidence on market manipulations in less transparent markets such as China and Pakistan (ibid). In their model, uninformed traders follow informed manipulators by buying on the rise. Thus in some sense these traders act as herds, free riding on others' information and exacerbating volatility in the process.

If prices do not reflect all the information, investors look elsewhere to fill the information gap. One natural place is to look for volume or the relative strength of sell-to-buy ratios. This is because such variables may tell uninformed investors of the behavior of the informed investors and thus contain information not otherwise available in opaque pricing when opacity is large. Thus, herd behavior will also arise in opaque markets.

If the above view is correct, then more transparent markets should be more stable and less subject to herd behavior. Yet, Furman and Stiglitz (1998) have argued that more transparency, which they interpret as a higher frequency of information release, could imply a higher, rather than a lower, price volatility. Bushee and Noe (2000) provide a mechanism for this claim by finding a positive association between corporate transparency and the volatility of the firm's stock price. They argue that firms with higher levels of disclosure tend to attract certain types of institutional investors which use aggressive, short-term trading strategies which in turn can raise the volatility of the firm's stock price.

This paper tries to explain these conflicting outcomes. The paper first develops a randomized analytical model in which investors follow both prices and also the behavior of each other. The latter leads to herd behavior in which cascades can develop as an aggregate systemic phenomenon. Because the resulting model with its randomization cannot be analytically solved, we simulate the model using Monte Carlo techniques. Here, we find that over time, episodes of stable behavior are interrupted by massive spikes in buy or sell behavior. The paper then empirically examines the model's simulated predictions with intraday volatility data along with a novel measure of transparency from the World Economic Forum that allows us to test the implications of the model with panel data for 2000-2009.

The model examines how herd behavior, driven by uncertainty about the degree to which prices actually reflect true information, can lead to financial cascades and dramatically larger stock market volatility. Traders actions are based on both the "previous period's" observed prices and on the behavior of other trading agents (both public information). There is a continuum of heterogeneous trading agents that are randomly differentiated according to two dimensions: their reservation values of the equity price *and* the aggregate sell-to-buy ratio of the equity in question. Ceteris paribus (i.e. considering each channel alone), if the equity price, or the aggregate sell-to-buy ratio, reach their reservation values for investor i, this will trigger a sell or buy action on the part of that investor. Naturally, the final decision will depend on the combination of both pieces of information which we will discuss later. What makes the aggregate sell to buy ratio to not perfectly correlate with prices, is the heterogeneity in trader behavior which leads to *different* interpretation of any given price. In fact Wang (1994) argues that the heterogeneity among investors is precisely what gives rise to volume behavior, implying that volume conveys important information about fundamental values.

While there is large literature on heterogeneous agents in financial markets (see Hommes 2006 for a survey), this paper is in the spirit of the behavioral model of Boswijk et.al (2007) in which agents differ, not in their having private information, but in their different interpretation of public information. Wang (1994) points out that investors trade among themselves simply because they are different. The extent to which agents rely on the aggregate buy/sell ratio reflect their herd behavior and stems from uncertainties about the accuracy of the price mechanism. We allow for agents to be update their reservation price over time, upon observing new market information. The resulting model suggests that for a wide range of a parameter value that represents the speed at which traders update their reservation values upon observing the market signals, an "inverted-U" effect of increased market transparency on volatility emerges, in which early improvements in transparency actually increase volatility, but beyond a certain point, sufficiently large increases in transparency lead to a decrease in volatility. The first (upward) portion seems to be consistent with the Furman-Stiglitz (1998) thesis in that more frequent news and information access intensifies volatility, while the second (downward) portion of the inverted-U follows the more conventional wisdom in which transparency reduces volatility, exemplified by the quote cited earlier from the International Monetary Fund.

To empirically test our results, we need detailed stock market data, a good measure of transparency, and various other controls. One of the challenges in the way of examining transparency hypotheses in economic and political science literature has been the lack of systematic transparency data over time. We are able to address this shortcoming by compiling and transcribing two very specific indicators of financial transparency from the World Economic Forum (WEF) annual reports. The two measures are: the strength of accounting and audit standards and the transparency of government policy. Financial Volatility is measured for 2000-2009 by detailed intraday stock market data for 23 advanced and emerging market economies. A number of important controls (e.g., measure of market liquidity) are also included and discusses in the empirical section. Both measures of transparency that are derived from the WEF strongly support our theoretical findings and are generally robust with respect to various empirical specifications.

In what follows, Section 2 describes the analytical model; Section 3 presents the model and its Monte Carol simulations; Section 4 presents the empirical evidence; and section 5 provides the concluding remarks.

2 Model

The focus of our model is the actual act of trading in equity markets since it is ultimately the action of buying and selling that determines the equity prices. Given this focus, we will make no distinction between the underlying intentions of market participants such as traders, investors, or speculators and instead focus on the act of buying and selling. There are two types of information in the market, the equity price and what may be a proxy for the equity price momentum, the sell-to-buy ratio. If the price signal is fully informative, the sell-to-buy ratio should contain no new information and will not be used by traders. But to the extent that price mechanism may be opaque or, at times of great uncertainty, subject to large volatility, the sell-to-buy ratio may contain useful information and may be relied on more heavily. In general, then, both the price and the sell-to-buy ratio will be used by any given trader, with the weight on each influenced by the degree to which the price mechanism is opaque or subject to large uncertainty. (It will be shown, however, that unlike the self equilibrating character of the price mechanism, the sell-to-buy mechanism is potentially unstable). Alternatively, this framework can be cast by assuming two classes of traders, informed and uninformed, with the former relying on prices and the later on sell-to-buy ratios and imagining the fraction of uninformed traders rising with price opacity/uncertainty. The result will be the same for our analysis. But we feel that the former is more realistic as both types of information are often used at all times by the market participants but to different degrees. Thus, this is the framework which we use.

The behavior of traders is governed by their "reservation" values of the equity prices and of sell-to-buy ratios. The "reservation" price reflects traders' subjective (see below) valuation of the fundamental value of an equity. When the observed price exceed this fundamental subjective valuation, it will trigger a sell action; and when it is less than this fundamental subjective valuation, it will trigger a buy action, as we will see below. The reservation sell-to-buy ratio is a convenient tool to allow us to study the herd behavior. This reservation value reflects the traders' subjective (see below) expectation of the market weakness or (negative) momentum regarding a stock. When the actual (observed) ratio exceeds traders' subjective expectation, a sell action, and when it is less, a buy action is triggered, ceteris paribus. We use the term ceteris paribus, here, as the price and the momentum information are assumed independent and orthogonal. In the end, a decision is based on the weighted average of both channels. Note that in the absence of herd behavior and with full information, subjective valuation would converge to actual price in the long run. But in the presence of price inefficiencies (opacities) her behavior matters and thus convergence may not result.

To generate trading behavior where but some wish to sell while others wish to buy, while all face a common price and a common sell-to-buy ratio, traders must somehow differ in some respect. Since information is common, agents can be heterogeneous only in their interpretation of the market information to generate their unique "reservation" price or "reservation" sell-to-buy values. One way to do this, is to posit that agents possess some private information (see Hommes, Cars 2006). In Boswijk et. al. (2007) agents differ, not in their having private information, but in their different interpretation of public information. Regardless of the reason why, we assume that these differences among agents result in differences in their "reservation" values along the two dimensions described above. We assume that there is a continuum of heterogeneous agents who are randomly distributed and who differ only in these two respects.

Preferences are expressed by the continuum of reservation prices and reservation sell-to-buy ratios above and below which decisions must be made to buy or sell equities. The sell or buy trigger points depend on these reservation values and on the observed equity prices and sell-to-buy ratios. This trigger point is updated each period, given market information. But we also allow for the possibility that agents may update their reservation price next period upon observing new actual prices. The introduction of sell-to-buy ratios reflects the key notion that when the environment is sufficiently uncertain, as a consequence either of stress states or of inadequate institutional framework for transparency, then the belief that prices reflect full information is weak, thus partially supplanted by the consideration of the behavior of other market participants..In practice, this is consistent with evidence from trading algorithms and trading behavior. It is of course also related to the classic information free rider problem known as the Grossman-Stiglitz paradox, originally associated with the critique of the efficient market hypothesis (Grossman and Stiglitz, 1980).

2.1 The Price Channel

We begin with the treatment of the more intuitive price channel and leave the treatment of the more unusual herd channel for the next subsection, even though both treatments are similar. To pin down the ideas, let m and n denote the observed number of sellers and buyers, respectively, at any given market price. For ease of analysis, each seller or buyer is assumed to engage in the sale or purchase of only one unit of equity. It is not too difficult to generalize this to the case where volume matters and sellers and buyers vary in the volume of orders, but adding this factor will only complicate the salience of the model without adding additional insight or substance.

Agents are randomly distributed according to their unique reservation price P_r with a probability density function, $g(p_r)$at any given time. For any observed price P_t at any moment in time, agents are divided into two types; those with a reservation price less than or equal to the observed ratio, $P_r \leq P_t$ and those with a reservation price exceeding P_t, that is $P_r > P_t$. To simplify exposition, we use subscript r to denote not only the reservation values but also the index of agents (thus agent r has reservation price P_r). Upon observing P_t agents of the first type will engage in selling (offering) their position and those of the second type will engage in buying a new position: For agents of the first type, this follows a general upward sloping supply behavior where more is offered as price rises, while for agents of the second type a rise is perceived to constitute a signal of higher innate value of the equities, leading these agents to engage in further buying of equities.

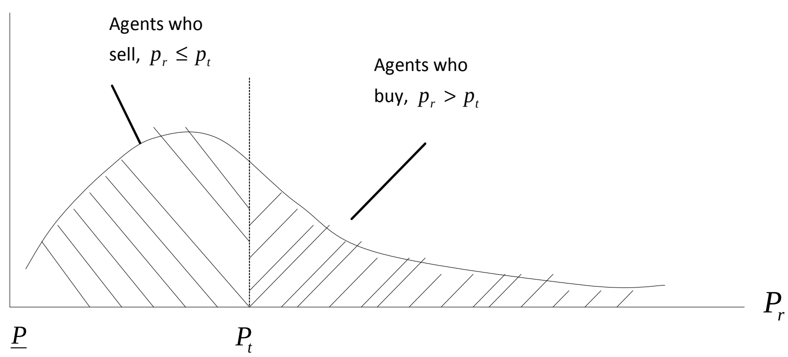
Consider investor r (we use the same index r to distinguish investors as we use to distinguish the reservation prices since, along the price channel, this is the only source of investor heterogeneity.) Thus, focusing on the price channel only for the present, let $U(P_t - P_r)$ represent the utility of investor r with $U' > 0$ and $U(0) = 0$. Given a price observation, P_t for type I investors, if $P_r \leq P_t$ the resulting non-negative utility $U^I(P_t - P_r) \geq 0$ can only be maximized if these investors sold their position and realized P_t. For type II investors, if $P_r > P_t$ a positive utility $U^{II}(P_r - P_t) > 0$ can be only be maximized if these investors engage in (additional) purchase of stocks. In short,

$$U^{*I} = Max[U^I(P_t - P_r), 0] \rightarrow \text{Sell when } P_t > P_r; \text{ otherwise do nothing}$$

$$U^{*II} = Max[U^{II}(P_r - P_t), 0] \rightarrow \text{Buy when } P_t < P_r; \text{ otherwise do nothing}$$

Given the random distribution of investors/traders with respect to their interpretation of market information and thus their reservation prices, agents actions can be depicted by a probability distribution function in Figure 1. (We have assumed that P is strictly positive.)

Figure 1: Probability Distribution of Agents Based on Reservation Price



To understand the process better suppose that the price increases. This would result in two effects: First, the mass of the distribution to the left of the P_t line increases and that to its right declines. This simply means that given their original reservation price, some agents who wanted to buy are no longer buying and more agents are willing to sell. Let us call this, the *"probability-mass transfer effect"*. However, as stated previously, reservation prices change and can be updated over time, given the change in price level. This leads to a second effect which shows up next period. Upon observing the increase in P_t, some agents who would have wanted to sell their positions, will have second thoughts because observing the actual price increase, their reservation price P_r at which they would have sold their position will increases, delaying a sell decision. This affects the probability mass of agents to the left of the observed price (and also by implication the probability mass of those to the right of the observed price). Putting this in probability terms the two states (1) and (2) can be compared in terms of the shift of the probability mass:

$$g^{(2)}(P_r \mid P_r \leq P_t < P_{t+1}) < g^{(1)}(P_r \mid P_r \leq P_t)$$

We call this effect, the *"preference update effect"*. Note that the two effects work in opposite directions: a rise in the price will induce some to sell (a normal upward sloping supply response), while it will induce others to hold their positions or to buy more. Since prices are also affected by supply or demand for stocks, as we will see later, this means that the price channel itself may be stabilizing or destabilizing. It is stabilizing if the mass transfer effect dominates, but destabilizing if the preference update effect dominates. This is an important point since it has the potential implication that cascades can be produced as a result of price as well as herd effects. Verifying this potential will have to await the full model development and its simulation.

Two points are worth noting. First, exiting the market by neither selling nor buying does not pose a problem for our distribution. This is because the support for the distribution does not assume a fixed number of participants. All that is required is that an any given time and for any observed value of P_t, there are $g(P_t)$ fraction of market participants whose reservation price is given by $P_r \leq P_t$ and $1 - g(P_t)$ fraction whose reservation price is given by $P_r > P_t$. Second, whether or not prices have risen or fallen from the last period, will change the distribution via the preference update effect only when g is compared to its value in the last period. But the contemporaneous shape of g will not be affected. Later, when we choose a Pareto distribution to represent g, this is reflected by a change over time in the value of the parameter of Pareto distribution itself depending on whether prices have risen or not from previous period. But the contemporaneous integrity of Pareto is not affected at any moment in time.

The above results can be written as follows:

$$m_{t+1}(P_t) \mid_{price\ channel} = \int_{\underline{P}}^{P_t} g(P_r \mid P_t) dP_r \tag{1}$$

$$n_{t+1}(P_t) \mid_{price\ channel} = \int_{P_t}^{\infty} g(P_r \mid P_t) dP_r \tag{2}$$

Let η_t denote the ratio of sellers to buyers at any time, t, such that

$$\eta_t = m_t / n_t$$

Then we can write:

$$\eta_{t+1}(P_t)\mid_{price\ channel}= \frac{m_{t+1}(P_t)}{n_{t+1}(P_t)} = \frac{\int_{\underline{P}}^{P_t} g(P_r \mid P_t)dP_r}{\int_{P_t}^{\infty} g(P_r \mid P_t)dP_r} \tag{3}$$

We will return to this when calibrating the model for a specific distribution.

2.2 The Herd Channel

First, we suppose that the herd channel is the only channel available, in order to simply to present the methodology in this ceteris paribus manner. We will then incorporate both channels into the agents' behavior. The methodology is similar to the price channel, but the outcome is distinct in that it produces a positive feedback mechanism that eventually feeds the market instability of the model. With respect to the structure of probability densities, similar to the price channel, agents are again also assumed to be randomly distributed along a variable η_r (explained below), with a probability density function $f(\eta_r)$. The variable η_r denotes both agents "reservation value" of the sell-to-buy ratio, η as well as the index of agent with that reservation value (following same scheme as in price channel). For any observed value of η_t at any time t agents are distinguished by two types; those with a reservation ratio less than or equal to the observed ratio,

$$\eta_r \leq \eta_t$$

and those with a reservation ratio exceeding the observed ratio,

$$\eta_r > \eta_t$$

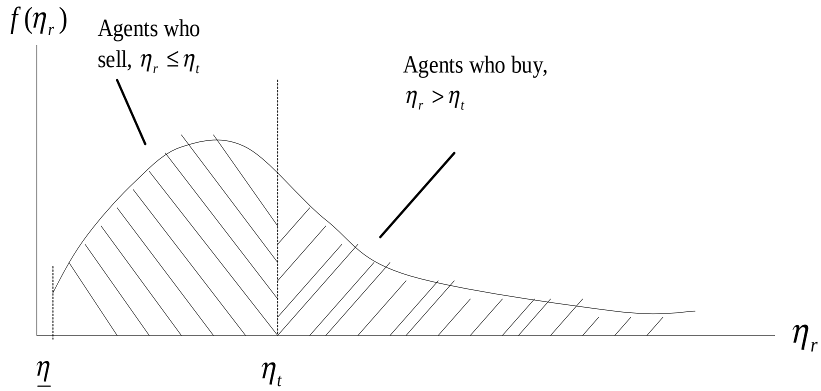
For agents of the first type the current observed number of sellers relative to buyers is too high, given their risk perspective. Thus, upon observing η_t agents of the first type will engage in selling their position thus reinforcing next period value of η_t .Agents of the second type consider the current observed sell-to-buy ratio η_t not high enough, given their risk perspective. Thus they continue to engage in buying stocks, further reducing the next period value of η_t. The herd mechanism can be presented in a similar utilitarian framework as the price channel: Let $V(\eta_t - \eta_r)$ represent the utility of investor r with $V' > 0$ and $V(0) = 0$. Given an η_t observation, type I (II) agents, realize their maximum utility by selling (buying) shares:

$$V^{*I} = Max[V^I(\eta_t - \eta_r), 0] \rightarrow \text{sell if } \eta_t > \eta_r\text{; otherwise do nothing}$$

$$V^{*II} = Max[V^{II}(\eta_r - \eta_t), 0] \rightarrow \text{buy if } \eta_t < \eta_r\text{; otherwise do nothing}$$

This is depicted in Figure 2.

Figure 2: Probability Distribution of Agents Based on Reservation Values of Sell-to-Buy



Note that any exogenous increase in η_t will increase the number of agents of the first type and reduce those of the second type as the probability mass moves from left of η_t to the right of η_t. This is the "probability mass transfer effect" as was in the case of price channel. The higher value of η_t this period then increases next period's observed ratio, η_{t+1} creating a vicious cycle that is at the heart of financial cascades. Because action here is predicated upon observing the action of others, we call this channel the "herd channel". As in the case of the price channel, possible changes in the investors' reservation value of η_r upon observing η_t must also be considered. As before, call this the preference update effect. Let us once more re-examine the effect of an increase in η_t. This increase would cause agents, potentially on the buy side of the distribution ($\eta_r > \eta_t$), to reduce their reservation value of η_r and thus postpone/cancel their purchase decisions. An inequality relationship in probability mass similar to the price mechanism holds such that

$$f^{(2)}(\eta_r|\eta_r > \eta_t; \eta_t < \eta_{t+1}) < f^{(1)}(\eta_r|\eta_r > \eta_t)$$

But unlike the Price channel this preference update effect, actually reinforces the probability mass transfer effect thus intensifying the potential for a cascade. (In figure 2 both effects reduce the probability mass to the right of the observed η_t.) Thus, the herd mechanism is unambiguously destabilizing.

From the above description, focusing on the cascading channel, the total number of sellers and buyers at $t+1$, given the behavior of market participants at t, is given by:

$$m_{t+1}(\eta_t)\ |_{herd\ channel} = \int_{\underline{\eta}}^{\eta_t} f(\eta_r|\eta_t) d\eta_r \tag{4}$$

$$m_{t+1}(\eta_t)\mid_{herd\ channel}=\int_{\eta_t}^{\infty} f(\eta_r|\eta_t)d\eta_r \tag{5}$$

where η in equation (4) stands for the minimum (threshold) value of η. (We assume that there are always some, if very few, sellers, i.e., $\eta > 0$). From equations (4) and (5) it follows that,

$$\eta_{t+1}\mid_{herd\ channel}=\frac{m_{t+1}}{n_{t+1}}=\frac{\int_{\eta}^{\eta_t} f(\eta_r)d\eta_r}{\int_{\eta_t}^{\infty} f(\eta_r)d\eta_r} \tag{6}$$

2.3 Combining Both Effects

We now come to the combining the two channels, as in reality agents are likely to utilize both channels of information. Suppose a decision to buy and sell takes into account the herd channel with a weight θ ($\theta\epsilon[0,1]$) and the price channel with a weight factor of $1-\theta$ (More about θ later). Define a grand utility function, W, such that:

$$W = \theta \cdot V + (1-\theta) \cdot U$$

Now, it is clear that if it were possible for a sell (buy) decision to occur under *both* the price and the herd channel, both V and U would be maximized under a *consistent* (same) action set (either sell under both channels or buy under both channels). In that case, W is naturally also maximized under that action set. The difficulty arises when the investor is bullish (bearish) under the price channel and bearish (bullish) under the herd channel. In this case, the size of weight factor, θ, and the two distance measures, $|P_t - P_r|$ and $|\eta_t - \eta_r|$, determine the ultimate decision of each investor.[3] But this complexity does not concern if we are interested in the *aggregate* sell to buy ratio. To do so, define Θ as aggregate analog of θ across investors, given a priceP_t:

$$\Theta = h(\theta|P_t, \int P_r.dP_r)$$

with $h' > 0$. Then we can express the aggregate buy-sell ratio as follows:

[3] To illustrate this difficulty, suppose observing p_t an agent r for whom $p_t > p_r$ is bearish and would engage in selling, but observing η_t same agent would experience $\eta_t < \eta_r$ thus should be bullish and engage in buying. Then a sell action would mean $U > 0$ but such an action would cause $V < 0$ so that $W = \theta U + (1-\theta)V > 0$ iff $\frac{\theta}{1-\theta} > -\frac{V(P_t - P_r)}{U(\eta_r - \eta_t)}$. Thus θ, the shape of the utility functions, and the distances $|P_t - P_r|$ and $|\eta_t - \eta_r|$ determine the ultimate sell decison.

$$\eta_{t+1} = \Theta\eta_{t+1}|_{herd\ channel} + (1-\Theta)\eta_{t+1}|_{price\ channel} = \Theta\frac{\int_{\eta}^{\eta_t} f(\eta_r)d\eta_r}{\int_{\eta_t}^{\infty} f(\eta_r)d\eta_r} + (1-\Theta)\frac{\int_{P}^{P_t} g(P_r)dP_r}{\int_{P_t}^{\infty} g(P_r)dP_r} \quad 0 \leq \Theta \leq 1 \quad (7)$$

One can think of Θ as an indication of the weight that market as a whole would put on prices and $1-\Theta$ the weight that market as a whole would put on investor behavior. Appendix 1 develops a framework that shows how Θ is related to the opacity of the markets. Intuitively, Since in highly uncertain times, or highly non-transparent states of the market, prices are not as informative, reliance on other investor's behavior (the herd channel) becomes more prominent as a carrier of information. Thus, a large Θ would indicate inefficient market signal transmissions for either reason. Later, we model this aspect by linking a parameter that indicates uncertainty about the accuracy of the price mechanism to the herd coefficient, Θ. We will then take advantage of that linkage to construct our empirical test of the implications of the model.

2.4 Price adjustment mechanism

Another key component of the model is the role of the price adjustment mechanism. We assume that prices are subject to two forces; (1) the usual Geometrical Brownian Motion as indicated by the Wiener process and a (2) response function to sell-to-buy ratio, analogous to economists' excess demand function. To integrate these two forces, we rely on the modified form of a recent innovation by Jarrow and Protter (2005). Jarrow and Protter consider the pricing of an equity at time t to be a function of the stock holdings of the trader, and decompose this into a competitive and what they call a supply function. Adopting their approach to the problem at hand, the price $P(t, \eta_t)$ can be decomposed into two components, an inverse response function of prices to sell-to-buy ratio say $G(\eta_t)$ (with $G\prime{<}0$) which is similar in behavior to an "excess demand function" and generates the stability in the system when tied to the supply mechanism in equation (7); and a "base" function $P(t, \eta_t = 0)$ that follows the classic Geometric Brownian Motion and is represented by the Wiener process. Thus we have:

$$P(t, \eta_t) = P(t, 0).G(\eta_t)\ G' < 0 \quad (8)$$

$$dP(t, 0) = P(t, 0)\mu dt + Pt, 0)\sigma\epsilon\sqrt{dt} \quad \varepsilon\tilde{}N(0, 1) \quad (9)$$

where, μ is the drift and σ is volatility of the equity. We convert both these equations to a discrete format so as to conform to a dynamic simulation approach which we will be utilizing later:

$$P_t(\eta_t) = P(0).G(\eta_t) \quad (10)$$

$$\Delta P_t(0) = P_t(0)\mu\Delta t + P_t(0)\sigma\epsilon\sqrt{\Delta t} \quad \varepsilon\tilde{} N(0,1) \quad (11)$$

We may note that instead of a stochastic volatility form such as GARCH, the volatility of $P(0)$ is assumed constant here, given by σ. This is because we intend to focus on volatilities that are *endogenously* generated at the aggregate level by the model, showing up ultimately in $P_t(\eta_t)$. Thus, we want to abstract from imposing any external volatility generating form exogenously. As we will see, our final volatility of $P_t(\eta_t)$ does depict stochastic volatility characteristics under some specifications. With this discrete representation, we now add the final dynamic price equation,.i.e.:

$$P_{t+1}(0) = P_t(0) + \Delta P_t(0) \quad (12)$$

2.4.1 Functional Forms

To numerically simulate this model we will need the explicit form of the distributions. First we focus on the distribution of market participants according to their reservation values of sell-to-buy ratio and price, i.e., $f(\eta_r)$ and $g(P_r)$. We assume that both $f(\eta_r)$ and $g(P_r)$ can be reasonably characterized by a Pareto distribution. There are at least three reasons for this. First, we must have a left-bounded distribution. Second, the distribution should allow for tail behavior. This means two things: the possibility of large observed sell-to-buy ratio or prices (a bubble), and the possibility that no matter how large are these observed values, there are always some agents that would be buyers (agents with a tail attitude!). Third, in financial markets, Gabaix, et. al. (2006, 2008) find that the process underlying the distributions of the volume and returns follow Power Laws for large trades and explain that by the existence of large "market makers" (a process akin to ours). The key discovery in physics, known as Scale Invariance, has allowed both economists and physicists to be able to generalize the presence of Power Law in numerous physical and financial phenomena. Newman (2005) describes many such instances, ranging from word frequencies, to web hits, to magnitudes of earthquakes, and the intensities of wars. Spagat and Johnson and Spagat (2005) show Power Law at work in describing the number of attacked in a war, applying their analysis to the US war in Iraq. Mohtadi and Murshid (2009a, 2009b) show that a form of Power Law, in the form of extreme value distributions describes the instances of terrorism attacks. Thus the present perspective on the examination of power law follows a rich background of analysis and examination by physicists and economists. Finally, Pareto distribution is extremely analytically tractable.

If X is a random variable, a Pareto distribution is defined as, $prob(X \geq x) = (x_m/x)^{\beta}$where x_m is the minimum admissible (threshold) value of X. The corresponding cumulative distribution function is $G(X < x) = 1 - (x/x_m)^{\beta}$. Let the random variable X represent the agent's reservation price ($X = P_r$), the point x represent the observed (actual) equity price ($x = P_t$), the lower threshold x_m represent the minimum feasible positive lower bound of equity price ($x_m = \underline{P} > 0$).Then,

$$prob(P_r \geq P_t) = (\underline{P}/P_t)^{\beta}$$

and the corresponding cumulative distribution function is,

$$G(P_r < P_t) = 1 - (\underline{P}/P_t)^{\beta}$$

with β as the parameter of the Pareto distribution. However, as we have seen the reservation price might evolve over time, given an observation of a price change. We saw before that for the case of the price channel, this reservation update effect works in reverse to the probability mass transfer effect (higher observed price gives some sellers pause). To capture this evolution, we let β depend on observed price changes,

$$\beta = \beta(P_{t+1}/P_t) \text{ with } \beta'(.) \geq 0$$

where equality reflects no change in the reservation price. In this formulation, it is easy to see that while $\partial G/\partial P_t$ remains positive, reflecting the mass transfer effect (fewer people with reservation price below P_t are willing to sell when P_t is higher), $\partial G/\partial P_{t+1} \leq 0$, reflecting the effect of reservation update on *reducing* the fraction of sellers in response to the price *increase*. The probability mass of sellers, buyers and their ratio (via the price channel) is given thus by:

$$m_{t+1} \mid_{price\ channel} = G(P_r < P_t) = 1 - (\underline{P}/P_t)^{\beta(P_{t+1}/P_t)} \tag{13}$$

$$n_{t+1} \mid_{price\ channel} = prob(P_r \geq P_t) = (\underline{P}/P_t)^{\beta(P_{t+1}/P_t)} \tag{14}$$

$$\eta_{t+1} \mid_{price\ channel} = \frac{G(P_r < P_t)}{prob(P_r \geq P_t)} = \frac{1 - (\underline{P}/P_t)^{\beta(P_{t+1}/P_t)}}{(\underline{P}/P_t)^{\beta(P_{t+1}/P_t)}} \tag{15}$$

Similarly, if we let the random variable X denote the trader's reservation sell-to-buy ratio, $X = \eta_r$ the upper point x by the observed (actual) sell to buy ratio, $x = \eta_t$ and the lower threshold by $x_m = \underline{\eta}$, then from Pareto and its corresponding cumulative distribution the probability mass corresponding to the number of sellers and buyers (via the herd channel) are identified as

$$prob(\eta_r \geq \eta_t) = (\underline{\eta}/\eta_t)^{\gamma}$$

and

$$F(\eta_r < \eta_t) = 1 - (\underline{\eta}/\eta_t)^{\gamma}$$

The preference update effect is modeled similarly, with one notable difference: A rise in η_{t+1} must lower the probability mass to the right of η_t. This would be achieved if

$$\gamma = \gamma(\eta_{t+1}/\eta_t) \text{ with } \gamma'(.) \leq 0$$

The probability mass of sellers, buyers and their ratio (via the herd channel) is given by:

$$m_{t+1} \mid_{herd} = F(\eta_r < \eta_t) = 1 - (\underline{\eta}/\eta_t)^{\gamma(\eta_{t+1}/\eta_t)} \tag{16}$$

$$n_{t+1} \mid_{herd} = prob(\eta_r \geq \eta_t) = (\underline{\eta}/\eta_t)^{\gamma(\eta_{t+1}/\eta_t)} \tag{17}$$

$$\eta_{t+1} \mid_{herd} = \frac{F(\eta_r < \eta_t)}{prob(\eta_r \geq \eta_t)} = \frac{1 - (\underline{\eta}/\eta_t)^{\gamma(\eta_{t+1}/\eta_t)}}{(\underline{\eta}/\eta_t)^{\gamma(\eta_{t+1}/\eta_t)}} \tag{18}$$

The weighted average of the two mechanisms is given, as in equation (7), can now be specified using the Pareto functional form:

$$\eta_{t+1} = \Theta \frac{1 - (\underline{\eta}/\eta_t)^{\gamma(\eta_{t+1}/\eta_t)}}{(\underline{\eta}/\eta_t)^{\gamma(\eta_{t+1}/\eta_t)}} + (1 - \Theta) \frac{1 - (\underline{P}/P_t)^{\beta(P_{t+1}/P_t)}}{(\underline{P}/P_t)^{\beta(P_{t+1}/P_t)}} \tag{19}$$

2.5 The Price Response

A general equilibrium focus on how prices are determined in the aggregate is often missing in the herd literature whose focus has been to model the herd behavior rather than to fully integrate that behavior into the economy. To close this gap and to also tie the aggregate market uncertainties to herd behavior, we assume a sort of "or excess demand function" that specifies the relation between prices and the sell-to buy ratio. We assume a constant elasticity format for this function, as follows:

$$G(\eta_t) = 1 + \eta_t^{-\alpha} \tag{20}$$

where α is a random variable,

$$\alpha\tilde{\ } N(\alpha_o, \sigma_\alpha^2) \tag{21}$$

and where,

$$\sigma_a = m.\Theta \Rightarrow \Theta = (1/m)\sigma_a \tag{22}$$

with m as a constant parameter. To explain, there is an uncertainty in the efficiency of the price response mechanism which is what leads to a financial cascade (i.e., free riding of information off others) in the first place. Thus the uncertainty about the efficiency of price response, and herd behavior are linked through this equation. This becomes clearer if we view (22) in its equivalent form $\Theta = \sigma/m$. With this specification of the agents' behavior in equation (19), the stochastic price adjustment process in equations (10)-(12), and the stochastic inverse price response process in equations (20)-(22), we are in a position to examine how this system evolves. To do this, we formulate a simulation as described below.

3 Monte Carlo Simulation

The simulation revolves around randomizing two stochastic processes: the price adjustment process via the Wiener process and the herd process. We used Matlab to carry out the simulation program. For each choice of parameter value (see below) we ran up to 10,000 simulations for 100 time periods (corresponding roughly to 100 trading days). For a specific set of parameters described in Table 1 we choose values for Θ to vary from zero to 0.75. As explained before, Θ reflects agents' "subjective" probability of underlying market imperfection. This imperfection then triggers reliance on other agents' behavior as data points. Equation (22) makes it clear that Θ and the uncertainty about the market are linked. The value of daily volatility σ that is used in the Wiener process in (11) is chosen to correspond to the annual volatility of 16% ($.01\times\sqrt{256}$for 256 trading days on average). The drift parameter, as in the case of volatility parameter is based on an annualized rate of return for stocks. This long-term historical rate of return on stocks is about 8% leading to a daily value of.0003 ($08 \div 256 \cong .0003$). Parameter α_o is the base (mean) value of α per equations (20) and (21) representing the elasticity of inverse supply response. But the uncertainty that is associated with the market efficiency may trigger a cascading event. The model must be able to allow for this possibility (whether the simulation bears it out or not.) This is captured by linking α in (20) with the cascading behavior Θ. The parameter m that ties the stochasticity of α to cascading behavior Θ is chosen to be 2 (thus $\Theta = \sigma_\alpha/2$). We experimented with higher values of m such as 3 but they produced completely explosive outcomes. The functions $\beta(P_{t+1}/P_t)$ with $\beta' \geq 0$ and $\gamma(\eta_{t+1}/\eta_t)$ with $\gamma' \leq 0$ in equations (15) and (18) which represent the evolving coefficients of the Pareto distribution over time, are specified as follows: We would like to capture how rapidly/frequently agents update their preference structure represented by their reservation values of $P_r$and η_r. To do so we specify the functional forms of β and γ to reflect an elasticity value which we call ν and which we can increase or decrease to examine the impact of the agents' speed of preference update in our model. As it turns out, this single variable has the greatest impact in our model and one that is consistent with the evidence on OECD and emerging market. To keep the system simple we will assume that β and γ have the same functional form and parameter size with one being the negative of the other. This means the following:

$$\beta(P_{t+1}/P_t) = (P_{t+1}/P_t)^{\nu}; \quad \gamma(\eta_{t+1}/\eta_t) = (\eta_{t+1}/\eta_t)^{-\nu} \text{ with } \nu \geq 0 \tag{23}$$

We then allow the parameter ν to vary widely to represent differing reservation update speeds. In this way our Pareto distribution will have a variety of tails. The values of $\underline{\eta}$ and $\underline{P}$ are the threshold values of these parameters for use in their respective Pareto distribution. In the program that is written for this purpose, the evolution of prices and η are constrained to stay above these threshold values.

Table 1: Parameters and initialization

Preference update	ν	.30-.70
Daily volatility of stock price	σ	0.01
Initial value of price efficiency indicator α subject to randomization (its SD indicates high uncertainty about the price mechanism, thus low transparency)	α_o	1.00
Initial value of Pareto of Pareto distribution parameter for reservation price tied to preference update (ν) and price changes	β_o	0.9
Initial value of Pareto di Pareto distribution parameter for reservation sell-buy ratio tied to preference update (ν) and changes in sell-buy ratio	δ_o	0.9
Weight on herd versus price channel (tied to α)	Θ	0.05-0.80
Drift of stock price on daily basis	µ	0.0003
Lower bound threshold value of Pareto distribution for sell-buy ratio	$\underline{\eta}$	0.1
Lower bound threshold value of Pareto distribution for stock price	$\underline{P}$	0.1
Factor tying Θ α	M	2
Initial price and sell-buy ratio for the dynamics		1

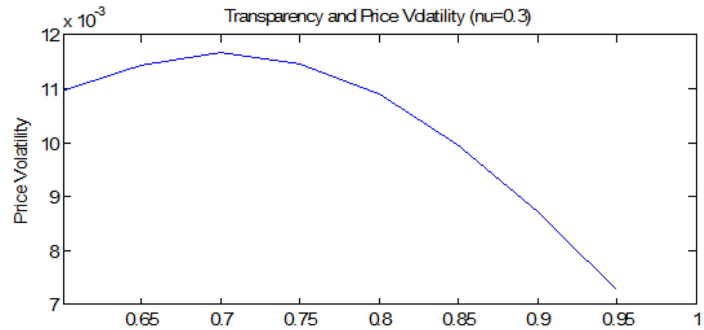
3.1 Simulation Outcome

Simulation results are presented in the three panels of figure 3. These correspond to three values of the reservation update parameter ($\nu = 0.3, 0.5, 0.7$). The vertical axis is the volatility (i.e., Standard deviation) of the prices as they *emerge* from the full model (i.e., not same as σ, as we discussed), while the horizontal axis (titled transparency) is inversely related to the standard deviation of alpha and thus also inversely related to the value of Θ. Results point to an inverted U: A rise in transparency initially increases volatility before it brings it down. In the first leg of the figures, we have high values of Θ (herd behavior is dominant). With greater transparency Θ falls. However, the inherent volatility in prices means that the greater reliance on the price channel (as $1-\Theta$ increases) does not necessarily lower volatility and in fact increases it. Eventually greater transparency conquers and price volatility falls (second leg). The explanation for the first leg of the curve is consistent with the Furman-Stiglitz effect (Furman and Stiglitz 1998) in which more transparency (which they interpret as a higher frequency of information release), increases price volatility. However, our finding here seems to suggest that this is not because of what Bushee and Noe (2000) called the competition among fund managers (a form of herd behavior) but because of the inherent price fluctuations. While herd behavior plays a key role in this process, its impact is not just direct, but also indirect acting via the price volatility that it seems to entail.

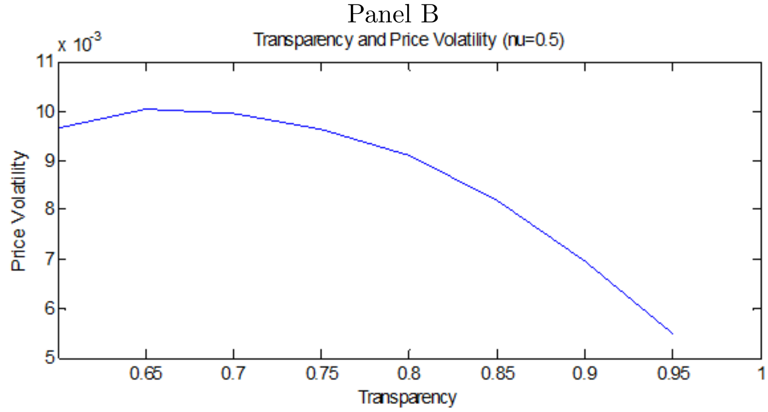
To check these result we compare the herd and the price volatility over 100 periods for the three cases. This is reported in panels of figures 4 and 5. Figure 4 depicts rather well the inherent "bubbles" associated with the herd behavior. This is seen by the dramatic, abrupt and short-lived spikes in herd volatility (i.e., sell to buy ratio η), interrupting otherwise smooth and stable stochasticity of η. By contrast, the price behavior over time, exhibits no dramatic spikes, but instead higher average volatility. Thus, while price seems consistent the GARCH variety (with a long run pivot), such an approach fails for the herd component of volatility. Finally, varying the reservation update parameter, ν, does not seem to make much of a difference in this qualitative description. However, we did also try extremely low values of $\nu = 0$ and $\nu = 0.1$ and found qualitatively different outcomes. Those results are not reported here in part because they are not supported by the empirical evidence that we will discussed later.

Figure 3-Transparency and Volatility (ν indicates the speed of reservation value updates)

Panel A



Panel B



Panel C

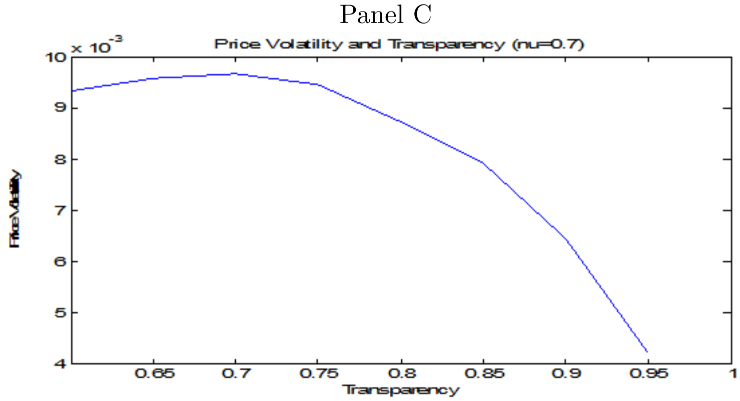
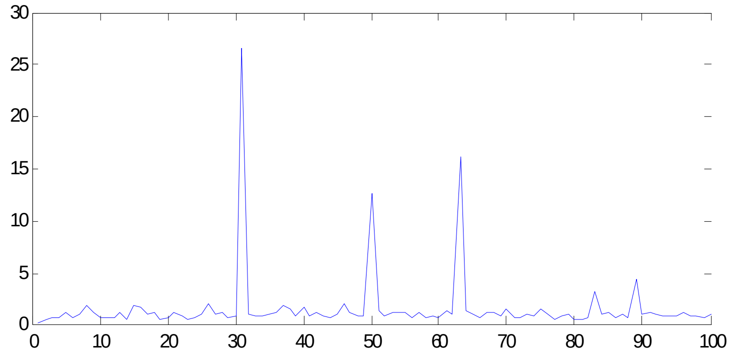


Figure 4- Herd Volatility over Time

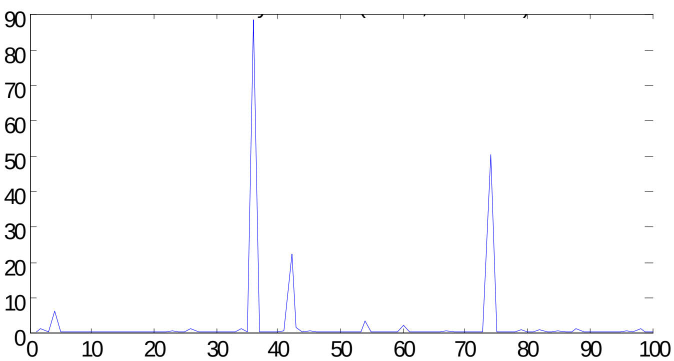
Panel A

speed of adjustment $\nu = .30$



Panel B

speed of adjustment $\nu = .50$



Panel C

speed of adjustment $\nu = .70$

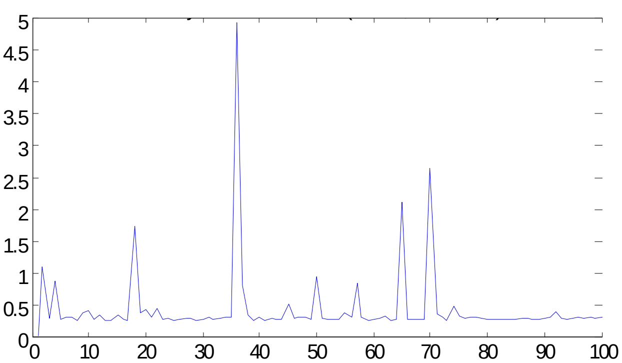
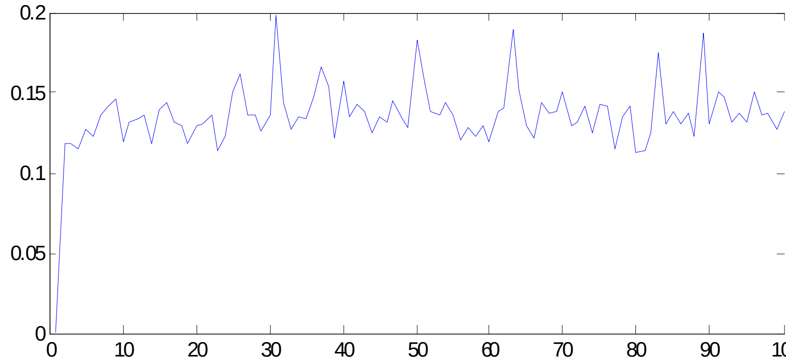


Figure 5- Price Volatility over Time

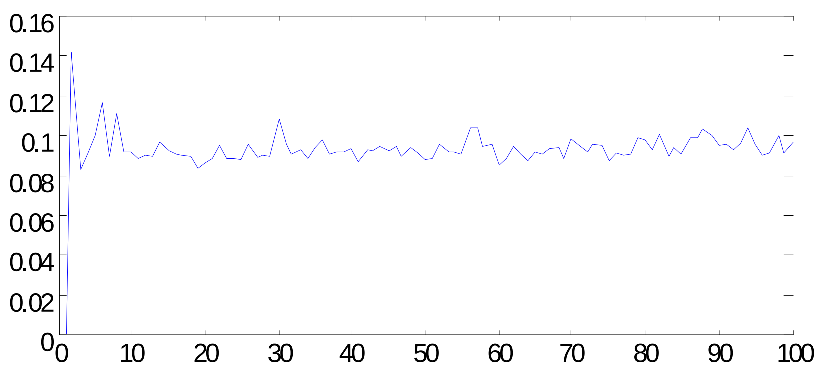
Panel A

speed of adjustment $\nu = .30$



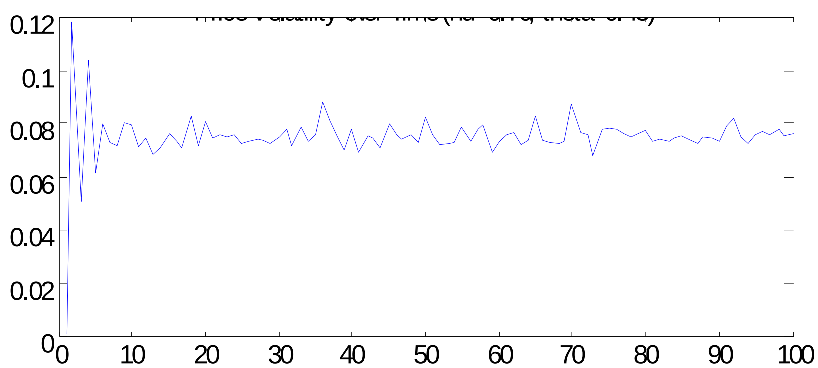
Panel B

speed of adjustment $\nu = .50$



Panel C

speed of adjustment $\nu = .70$



4 Empirics

In this section, we test the key prediction of the model, i.e. the inverted U prediction of the effect of transparency on volatility. One of the challenges that has stood in the way of examining various transparency hypothesis in the economics and political science literature has been the lack of systematic transparency data. The well known ICRG dataset does not include direct transparency measures. Other sources of transparency statistics either are not available systematically online, over time and across countries, or do not exactly measure transparency per se. We are able to uniquely address this shortcoming by compiling and transcribing two very specific indicators of financial transparency from the World Economic Forum annual reports. The two measures are: *the strength of audit and accounting standards* and the *transparency of government policy.*[4]

We construct an *intraday* stock market volatility measure to match the spirit of the theoretical results better. The intraday data is then annualized in order to match it to other key variables of interest and particularly the transparency variable which is only available on an annual basis (see below). The sample period is from 2000 to 2009 and covers 23 countries. The stock data are from Bloomberg and Yahoo. Additional controls such as stock market turnover (to control for the degree of liquidity) and volume of trade as well as a number of other controls are taken from Word Development Indicators. To isolate the role of financial institutional and transparency (or lack of) in financial volatility, we need to control for other drivers of financial volatility. One such major driver is international financial volatility. To control for this we include 3-month LIBOR rate.[5] This instrument has a key advantage over regional country specific instruments (e.g. domestic interest rates) in that it is independent of domestic financial markets whereas the volatility of domestic interest rates are not. Table 3 provides a descriptive statistic of the variables used.

4.1 Results

Tables 4-7 report the results of three different models, simple OLS regressions (as a benchmark), fixed effects panel regressions, and random effects panel regressions.[6] The first thing to notice is that the inverted U effect is strongly supported by the evidence and is quite robust, in all three models. To more

[4] Both variables are closely tied to financial transparency: The former for obvious reasons; the latter, because financial variables are highly sensitive to news about government policy and public announcements.

[5] See Appendix for a full definition of the variables and data sources.

[6] We corrected for heteroscedasticity in the errors. The fixed effects panel pertains to time fixed effect. Country fixed effects estimation yielded insignificant coefficients of the transparency variables, although in the same direction. Investigating further, we found very little variation in both transparency variables *within* countries, as compared to between countries, making a fixed-country effects estimation invalid. (We could not rely on the Hausman test to tell us between the fixed and random effects, because of the underlying initial heteroscedasticity in the error structure.)

rigorously examine the non-linearity associated with the inverted U effect, we use Lind and Mehlum's (2007) method of computing an extreme value (solution to quadratic equation), within the data range when the coefficients of the linear and nonlinear terms are significant. But as Lind and Mehlum correctly argue, this is a necessary, but not a sufficient condition for existence of u-shape. Thus, the standard test of joint significance of the linear and quadratic term is not completely adequate, and one needs more than just the joint significance of the two coefficients. Because of the composite nature of the hypothesis (a positive slope to the left of the extreme value and a negative slope to the right of the extreme value), Sasabuchi (1980) applies a likelihood ratio test to examine the non-linearity hypothesis. Our tables of results, discussed below, show both the value of the extreme, based on Lind and Mehlum (2007) as well as the likelihood ratio test based on Sasabuchi (1980) render support to the U-shaped curve.

Other insights are as follows: In the simple OLS, and the fixed effects regressions two results stand out: (i), trade, liquidity (measured by turnover ratio), and level of a country's development (measured by per capita income) all have a dampening effect on volatility; (ii) the size of the stock market (measured by stocks traded) increases volatility. In the random effects model, the 2008 financial crisis leads to higher volatility in all the tables. That the fixed effects estimation does not pick this up is of course consistent with the fact that the fixed effect panel is based on time-fixed effects. That trade is associated with *lower* volatility for the OLS and the fixed effects model, may be a consequence of complicated logic in which countries with greater trade share–notably NICs and BRICs- may be *less* well integrated into the world capital markets (c.f., Lane and Milesi-Ferretti, 2008). Integrated capital markets tend to synchronize financial volatility across countries and in doing so potentially amplify it.

5 Summary and conclusion

We have developed a randomized analytical model of financial cascades, i.e., information free ridership, in circumstances when uncertainty is high and markets are informationally opaque. We have numerically simulated this model, using a Monte Carlo method and discovered that at very limited transparency, an initial increase in transparency may initially increase volatility, but will eventually reduce volatility.

We have used two novel measures of transparency from the World Economic Forum annual reports that, to our knowledge, have not been used before, and in doing so have overcome data limitations constraining previous research on transparency. Since financial cascades flourish under extreme forms of uncertainty, they are likely to flourish in informationally and institutionally imperfect markets. We have examined this theoretical finding for the period 2000 to 2009. Our results are strongly supportive of the theory that volatility may initially rise with greater transparency but will eventually decline when sufficient transparency is introduced.

One final observation may be warranted: To the extent that one might think the "volatility bump" associated with initial rise in transparency is the phenomenon discussed by Furman and Stiglitz (1998) (more information leading to more short term trade and thus more volatility) one likely mechanism is that traders can update their reservation values rapidly. In our theory this means higher values of the parameter ν. But higher values of ν also clear markets better and reduce information traps described by Chari and Kehoe (2004). Lacking such mechanism, the eventual turn-around leg of the "volatility bump" would not occur since there is no mechanism to do so. One key implication: transparency and regulatory reform must be subsequent to market reforms to succeed. Future research can pin down some of these issues further.

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Table 2: List of Sample Countries

Argentina	France	Malaysia	Spain
Australia	Germany	Mexico	Sweden
Austria	India	Netherlands	Switzerland
Belgium	Indonesia	New Zealand	United Kingdom
Brazil	Israel	Norway	United States
China	Japan	Singapore	

Table 3: Descriptive Statistics

Variable	Observations	Mean	Std. Deviation.	Min	Max
GDP per Capita	215	19868.44	12791.97	452.969	42132.9
Trade	212	85.28996	77.40216	20.4854	438.092
Turnover Ratio	215	90.14269	59.00853	0.91426	348.581
Stocks Traded	215	83.38019	80.10185	0.888521	409.522
Libor 3-month (mean)	215	3.248308	1.847261	0.692142	6.528167
Strength of Audit and Accounting Standards	176	5.549432	0.7706025	3.4	6.6
Transparency of Government Standards	154	4.607792	0.8908051	2	6.3

Table 4. Transparency and Volatility: Average Daily High Minus Low

Dependent Variable: Annual Average of daily high minus low stock index value

	Strength of Audit			Transp. of Gov't Policy		
	OLS	FE	RE	OLS	FE	RE
	(1)	(2)	(3)	(4)	(5)	(6)
Transparency	1113.0***	1030.4***	153.07*	226.39**	247.29**	163.11
	(271.37)	(260.59)	(85.594)	(98.166)	(101.79)	(105.92)
Transparency2	-109.56***	-100.92***	-19.004**	-28.054**	-31.151***	-18.096
	(26.889)	(25.648)	(8.2095)	(11.142)	(11.770)	(11.584)
Trade	-0.6704***	-0.6775***	-0.5493	-0.5147***	-0.4722**	-0.6120
	(0.1932)	(0.1994)	(0.3903)	(0.1902)	(0.1935)	(0.4758)
Turnover Ratio	-0.8890***	-1.0032***	-0.4135	-0.9591***	-1.1235***	-0.3077
	(0.2821)	(0.3046)	(0.5140)	(0.2926)	(0.3231)	(0.5744)
Stocks Traded	0.3141**	0.3006**	0.3743	0.3578***	0.3812**	0.2983
	(0.1321)	(0.1402)	(0.3604)	(0.1328)	(0.1528)	(0.3808)
Log(GDP per Capita)	-24.071**	-25.378**	-7.7455	-26.238**	-24.196**	-22.415
	(11.156)	(11.087)	(18.017)	(11.088)	(10.346)	(18.571)
Libor 3-month (mean)	12.972	8.7598	7.9225	12.194	0.9532	8.5835
	(9.7236)	(17.450)	(6.2445)	(10.403)	(17.387)	(6.8507)
Financial Crisis Dummy (2008=1)	117.88	79.726	121.04**	131.69	75.215	117.92**
	(79.906)	(88.042)	(55.338)	(85.166)	(90.267)	(53.168)
Constant	-2348.3***	-2082.0***	-67.631	-21.614	33.372	-24.738
	(599.94)	(585.11)	(301.19)	(228.03)	(239.26)	(252.09)
R2	0.221	0.233	0.110	0.146	0.177	0.111
N	174	174	174	152	152	152
U-shape joint significance p-value	0.0003	0.0006	0.0585	0.0316	0.0238	
Sasabuchi test of u-shape p-value	0.000	0.0000909	0.0546	0.0137	0.0102	
Estimated extreme point, Bounds of Fieller interval	5.08 [4.94, 5.24]	5,10 [4.96, 5,27]	4.03 [-1.90, +6.82]	4.03 [2.35, 4.79]	4.0 [2.56; 4.70]	

* p<0.10, ** p<0.05, *** p<0.01, panel estimation with heteroscedasticity robust standard errors; standard errors are presented in parenthesis, U-test was done using utest command in STATA, the interval for u-test was set to 1-7 the value range for strength of audit and transparency of government policy; we also report Fieller interval for extreme point; see also footnote 6 in the text for additional detail
Countries in this data set are: Argentina, Australia, Austria, Belgium, Brazil, China, France, Germany, India, Indonesia, Israel, Japan, Malaysia, Mexico, Netherlands, New Zealand, Norway, Singapore, Spain, Sweden, Switzerland, United Kingdom, United States

Table 5. Transparency and Volatility: SD of Daily High Minus Low

Dependent Variable: Annual standard deviation of daily high minus low stock index values

	Strength of Audit			Transp. of Gov't Policy		
	OLS	FE	RE	OLS	FE	RE
	(1)	(2)	(3)	(4)	(5)	(6)
Transparency	548.30***	507.01***	139.02**	116.06**	125.11**	83.007
	(138.16)	(133.66)	(63.979)	(48.825)	(50.901)	(51.067)
Transparency2	-53.822***	-49.483***	-14.687**	-14.220**	-15.544***	-9.2255*
	(13.665)	(13.140)	(6.5451)	(5.5704)	(5.8679)	(5.5826)
Trade	-0.3240***	-0.3280***	-0.2852	-0.2505***	-0.2329**	-0.3054
	(0.0982)	(0.1014)	(0.1958)	(0.0950)	(0.0977)	(0.2321)
Turnover Ratio	-0.3964***	-0.4519***	-0.1956	-0.4360***	-0.5147***	-0.1256
	(0.1483)	(0.1558)	(0.2657)	(0.1565)	(0.1659)	(0.3157)
Stocks Traded	0.1518**	0.1398**	0.1939	0.1715**	0.1774**	0.1485
	(0.0659)	(0.0705)	(0.1810)	(0.0678)	(0.0775)	(0.1982)
Log(GDP per Capita)	-15.173**	-15.774***	-11.011	-16.457***	-15.481***	-14.921
	(5.8712)	(5.7657)	(8.9990)	(5.7292)	(5.3687)	(9.3952)
Libor 3-month (mean)	7.5480	6.6292	5.0799	7.4206	2.9766	5.7081
	(4.8018)	(8.5238)	(3.7613)	(5.1297)	(8.3576)	(4.0795)
Financial Crisis Dummy (2008=1)	68.473	48.331	70.075**	74.874	46.430	68.495**
	(43.307)	(46.868)	(33.096)	(46.081)	(47.923)	(32.046)
Constant	-1138.1***	-1008.0***	-155.00	3.6885	30.342	12.900
	(306.37)	(300.01)	(143.21)	(114.60)	(120.26)	(136.68)
R2	0.227	0.240	0.120	0.160	0.188	0.128
N	174	174	174	152	152	152
U-shape joint significance p-value	0.0005	0.0009	0.0805	0.0344	0.0262	
Sasabuchi test of u-shape p-value	0.00001	0.00018	0.0296	0.0112	0.00929	
Estimated extreme point, Bounds of Fieller interval	5.09 [4.95,5.27]	5.12 [4.97, 5.30]	4.73 [2.34, 7.39]	4.08 [2.61, 4.91]	4.02 [2.69; 4.79]	

* p<0.10, ** p<0.05, *** p<0.01, panel estimation with heteroscedasticity robust standard errors; standard errors are presented in parenthesis, U-test was done using utest command in STATA, the interval for u-test was set to 1-7 the value range for strength of audit and transparency of government policy; we also report Fieller interval for extreme point; see also footnote 6 in the text for additional detail
Countries: Argentina, Australia, Austria, Belgium, Brazil, China, France, Germany, India, Indonesia, Israel, Japan, Malaysia, Mexico, Netherlands, New Zealand, Norway, Singapore, Spain, Sweden, Switzerland, United Kingdom, United States

Table 6. Transparency and Volatility: Week with Largest Average Daily High Minus Low

Dependent Variable: Most volatile week per year of daily averages of high minus low stock index value

	Strength of Audit			Transp. of Gov't Policy		
	OLS	FE	RE	OLS	FE	RE
	(1)	(2)	(3)	(4)	(5)	(6)
Transparency	2320.9***	2150.1***	491.03**	494.86**	534.90**	370.07*
	(582.66)	(558.33)	(234.57)	(203.10)	(213.13)	(208.43)
Transparency2	-226.46***	-208.54***	-53.321**	-60.407***	-66.369***	-41.320*
	(57.656)	(54.886)	(22.865)	(23.115)	(24.651)	(23.172)
Trade	-1.4018***	-1.4174***	-1.2195	-1.0733***	-0.9906**	-1.3061
	(0.4178)	(0.4311)	(0.8366)	(0.4042)	(0.4112)	(1.0083)
Turnover Ratio	-1.7585***	-1.9925***	-0.9129	-1.8892***	-2.2153***	-0.6561
	(0.6074)	(0.6501)	(1.3234)	(0.6337)	(0.6895)	(1.5308)
Stocks Traded	0.6936**	0.6550**	0.8638	0.7682***	0.8105**	0.6774
	(0.2808)	(0.3001)	(0.8915)	(0.2913)	(0.3348)	(0.9543)
Log(GDP per Capita)	-73.063***	-75.663***	-45.288	-73.933***	-69.855***	-64.757
	(25.549)	(25.176)	(40.693)	(25.171)	(23.758)	(42.011)
Libor 3-month (mean)	29.588	22.788	19.657	29.545	7.9009	22.851
	(20.439)	(37.000)	(14.260)	(21.800)	(36.755)	(15.384)
Financial Crisis Dummy (2008=1)	286.06	205.77	293.94**	311.87	198.38	286.64**
	(178.83)	(195.54)	(132.60)	(190.24)	(200.06)	(128.16)
Constant	-4764.7***	-4219.5***	-395.49	50.999	162.5	45.730
	(1282.4)	(1246.0)	(629.42)	(476.43)	(506.14)	(537.13)
R2	0.225	0.237	0.117	0.160	0.186	0.124
N	174	174	174	152	152	152
U-shape joint significance p-value	0.0003	0.0006	0.0648	0.0295	0.0244	0.2018
Sasabuchi test of u-shape p-value	0.00013	0.000202	0.0299	0.0085	0.00808	0.0522
Estimated extreme point, Bounds of Fieller interval	5.12 [4.99, 5.31]	5.16 [5.01; 5.36]	4.60 [1.14, 7.30]	4.09 [2.74, 4.89]	4.03 [2.79, 4.80]	4.48 [-Inf, +Inf]

* p<0.10, ** p<0.05, *** p<0.01, panel estimation with heteroscedasticity robust standard errors; standard errors are presented in parenthesis, U-test was done using utest command in STATA, the interval for u-test was set to 1-7 the value range for strength of audit and transparency of government policy; we also report Fieller interval for extreme point; see also footnote 6 in the text for additional detail
Countries: Argentina, Australia, Austria, Belgium, Brazil, China, France, Germany, India, Indonesia, Israel, Japan, Malaysia, Mexico, Netherlands, New Zealand, Norway, Singapore, Spain, Sweden, Switzerland, United Kingdom, United States

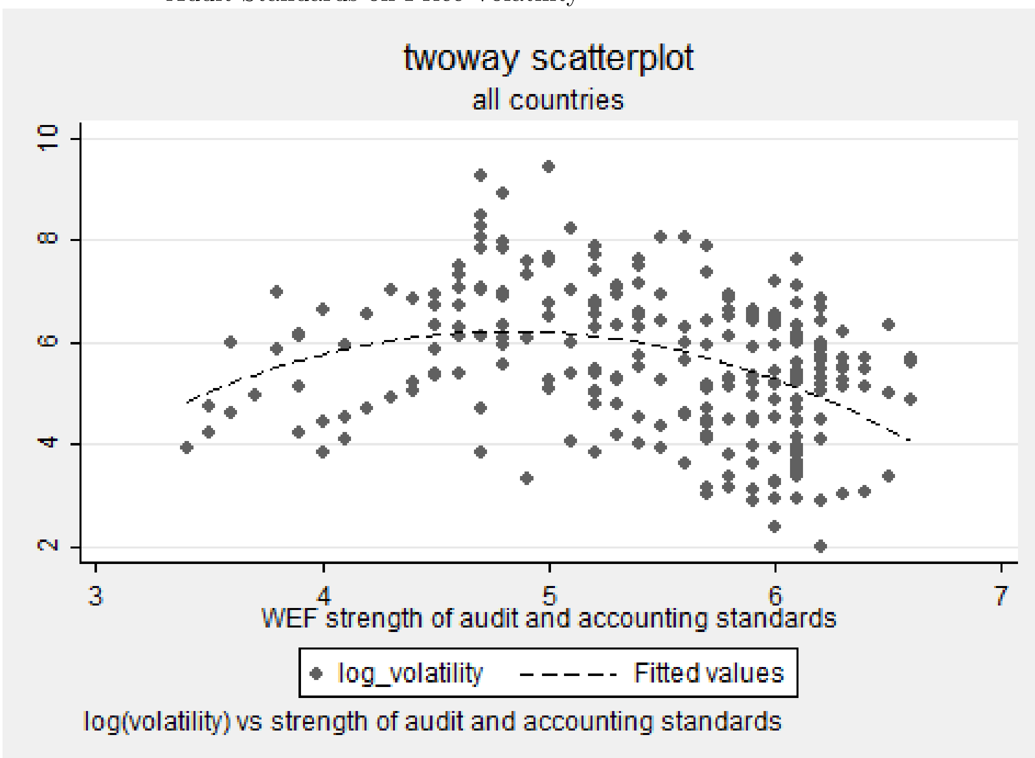
Table 7. Transparency & Volatility: Week with Largest Market Drop

Dependent Variable: Week with Largest Drop of Mon. open minus Fri. close

	Strength of Audit			Transp. of Gov't Policy		
	OLS	FE	RE	OLS	FE	RE
	(1)	(2)	(3)	(4)	(5)	(6)
Transparency	5007.4***	4649.1***	1294.2**	1153.0**	1241.7***	896.39*
	(1256.4)	(1226.2)	(586.30)	(454.37)	(474.28)	(485.30)
Transparency2	-492.13***	-454.44***	-137.65**	-139.37***	-152.30***	-97.495*
	(123.78)	(120.15)	(62.758)	(52.388)	(55.353)	(54.688)
Trade	-3.0565***	-3.0907***	-2.6114	-2.4734***	-2.3026**	-2.8471
	(0.9116)	(0.9397)	(1.6462)	(0.9183)	(0.9329)	(2.0247)
Turnover Ratio	-4.2296***	-4.7161***	-3.2628	-4.8094***	-5.5128***	-2.8749
	(1.4280)	(1.5139)	(2.6278)	(1.5126)	(1.6266)	(3.0104)
Stocks Traded	1.5862**	1.5068**	2.2992	1.8076**	1.9038**	2.0834
	(0.6874)	(0.7184)	(1.7954)	(0.7227)	(0.8001)	(1.9747)
Log(GDP per Capita)	-109.92*	-115.70*	-89.899	-125.01**	-116.59**	-144.94
	(61.114)	(61.363)	(94.279)	(55.584)	(53.906)	(98.323)
Libor 3-month (mean)	63.557	49.690	41.016*	63.677	16.855	45.980*
	(39.013)	(70.015)	(24.354)	(41.898)	(70.413)	(27.831)
Financial Crisis Dummy (2008=1)	816.41*	653.16	847.64**	877.20*	638.24	834.55**
	(431.52)	(460.18)	(358.24)	(458.98)	(470.28)	(348.71)
Constant	-10607.1***	-9470.9***	-1458.8	-363.66	-134.40	-47.763
	(2768.3)	(2736.7)	(1190.8)	(1018.8)	(1072.0)	(1182.5)
R2	0.236	0.246	0.155	0.172	0.197	0.168
N	174	174	174	152	152	152
U-shape joint significance p-value	0.0005	0.001	0.0861	0.0294	0.0232	0.1776
Sasabuchi test of u-shape p-value	0.00007	0.000152	0.0292	0.0071	0.0058	0.06
Estimated extreme point, Bounds of Fieller interval	5.09 [4.92, 5.27]	5.11 [4.94; 5.31]	4.70 [3.10, 7.52]	4.13 [3.05, 4.92]	4.08 [3.05; 4.83]	4.60 [-Inf, +Inf]

* p<0.10, ** p<0.05, *** p<0.01, panel estimation with heteroscedasticity robust standard errors; standard errors are presented in parenthesis, U-test was done using utest command in STATA, the interval for u-test was set to 1-7 the value range for strength of audit and transparency of government policy; we also report Fieller interval for extreme point; see also footnote 6 in the text for additional detail
Countries: Argentina, Australia, Austria, Belgium, Brazil, China, France, Germany, India, Indonesia, Israel, Japan, Malaysia, Mexico, Netherlands, New Zealand, Norway, Singapore, Spain, Sweden, Switzerland, United Kingdom, United States

Figure 7: Scatter Plot of the Impact of Accounting and Audit Standards on Price Volatility



Appendix 1: Herd Behavior: A Dynamic Micro Framework

Consider two states of the world, a transparent state (T) with probability ρ and an opaque state (O) with probability $1-\rho$. Individuals trade sequentially. They engage in S (sell) with probability π and B (buy) with probability $1-\pi$ when their actions are *independent* of previous players, but not so otherwise. To explain, if the world is characterized by T, trader k's actions are independent of those committed by previous trader $(k-1)'s$, but if the world is characterized by O, then trader k's actions are assumed to mimic those of trader $k-1$,with certainty (herd behavior), regardless of the kth trader's own private information. This simple model is similar to Bikhchandani and Sharma (2000) and Bikhchandani and Hirshleifer (1992), but with the difference that the in Bikhchandani and Sharma and Bikhchandani and Hirshleifer, the state of the world is not in question. Thus a Bayesian learning process, based on the signal observed from the investor k-1, tells the k'th investor indirectly something about the quality of the information that was available to k-1st investor, and if sufficient number of prior investors (as low as two) have decided to follow the same decision (in our case both S or both B), then the next investor would be more likely to follow suite regardless of his/her own decision. As such, the learning process in Bikhchandani and Sharma and Bikhchandani and Hirshleifer can converge quickly to a cascade, while the underlying environment is fixed. By contrast, we are interested in how the quality of the underlying environment influences the decision of the kth investor to supersede his/her own decision and follow suite. This makes our analysis both simpler, and somewhat more closely tied to the actual state of the world. Moreover, the learning process need not converge as quickly to a cascade, if the possibility that the state of the world is T is also allowed in. There are only two requirements for this to go through: (a) that such state is known to *all* participants and (b) that if T, then the private signal is of high quality and thus useful (no need for inference about others), while if O, then the private signal of kth individual is of such poor quality that the learning from $k-1'$st trader always improves k's signal. We will sketch the first few moves:

individual 1	S_1	B_1		
individual 2	$S_2 \vert T$	$B_2 \vert T$	$S_2 \vert S_1 \vert O$	$B_2 \vert B_1 \vert O$
individual 3	$S_3 \vert T$	$B_3 \vert T$	$S_3 \vert S_2 \vert O$	$B_3 \vert B_2 \vert O$
...				
individual k	$S_k \vert T$	$B_k \vert T$	$S_k \vert S_{k-1} \vert O$	$B_k \vert B_{k-1} \vert O$

We are then interested in the general probability of herd formation, $prob(S_k|S_{k-1}|S_{k-2}|...S_1)$ or $prob(B_k|B_{k-1}|B_{k-2}|...B_1)$ and the nature of the dependence of this probability on market opacity. We begin by studying first row and consider sell behavior only. The approach for analyzing the buy behavior is identical and will not be repeated here. We have,

$$\begin{aligned} prob(S_2|S_1) &= prob(S_2|S_1|T).prob(T) + prob(S_2|S_1|O).prob(O) \\ &= \pi.\rho + 1.(1-\rho) = 1 - \rho(1-\pi) \qquad \text{(A1)} \end{aligned}$$

where the first term on the right side of the first equality is $prob(S_2|S_1|T) = prob(S_2|T)$, due to the independence of the actions of trade 2 from trader 1, given state T. The probability of the action S is of course simply given by π. In other words under full transparency traders actions are entirely uncorrelated. By contrast, the term $prob(S_2|S_1|O)$ on the right side of the first equality is simply unity: Since under full opacity traders' actions are fully correlated, if trader 1 sells (S_1) trader 2 must surely also sell (S_2)[7]. Thus, $prob(S_2|S_1|O) = 1$. Continuing this procedure for period 3 we have:

$$\begin{aligned} prob(S_3|S_2|S_1) &= prob(S_3|S_2|S_1|T).prob(S_2|S_1|T).prob(T) \\ &\quad + prob(S_3|S_2|S_1|O).prob(S_2|S_1|O).prob(O) \\ &= \pi.\pi.\rho + 1.1.(1-\rho) = 1 - \rho(1-\pi^2) \qquad \text{(A2)} \end{aligned}$$

where, similar to the above, $prob(S_3|S_2|S_1|T) = prob(S_3|T) = \pi$ due to independence of trader actions under the transparency state, T and $prob(S_3|S_2|S_1|O) = 1$ due to full correlation of trader actions under opacity, state O.

By induction, generalizing from the above results to period/player k is now possible. We thus have:

$$prob\ (herd\ formation\ at\ k) = prob(S_k|S_{k-1}|S_{k-2}|...S_1) = ... = 1-\rho(1-\pi^{n-1}) \qquad \text{(A3)}$$

It is now clear that,

$$\frac{\partial prob(S_k|S_{k-1}|S_{k-2}|...S_1)}{\partial \rho} < 0 \quad \text{Q.E.D.} \qquad \text{(A4)}$$

[7] In Bikhchandani and Sharma and Bikhchandani and Hirshleifer, this probability is intially less than 1, since the private informtion of the trader in question may contradict the signal from previous sequence of traders. But this probability quickly rises to near unity, if the action of previous players are all in sink (which is the instance we are studying). Here, for simplicity the probability is taken to be one. This distinction makes little difference once k is sufficiently large.

Appendix 2: Definitions and Sources of Variables used in the Regression Analysis

Variable	Definition and Construction	Source
Coefficient of Variation	Monthly Stock Market Index Data, standard deviation of monthly stock index divided by monthly mean of stock index	Bloomberg, Yahoo
Volatility	Monthly Stock Market Index Data, standard deviation of monthly stock index	Bloomberg, Yahoo
Strength of auditing and accounting standards	Financial auditing and reporting standards regarding company financial performance in your country are (1=extremely weak, 7=extremely strong)	World Economic Forum, Global Competitiveness Report 2000-2009
Financial Market Sophistication	The level of sophistication of financial markets in your country is (1=lower than international norms, 7=higher than international norms)	World Economic Forum, Global Competitiveness Report 2000-2009
Transparency of government policymaking	Are firms in your country usually informed clearly by the government of changes in policies and regulations affecting your industry? (1=never informed, 7=always informed)	World Economic Forum, Global Competitiveness Report 2000-2009
Trade	Ratio of sum of Exports and imports to GDP	WDI, 2011
Turnover ratio	Total value of shares traded during the period divided by the average market capitalization for the period	WDI, 2011
Stocks traded, total value (% of GDP)	Ratio of total value of stocks traded to GDP	WDI, 2011
GDP per capita	Ratio of total GDP to population in constant 2000 US$	WDI, 2011
LIBOR 3 month	Mean of Annual LIBOR data for 3-months	Wall Street Journal and www.mortgate-x.com
Oil Price Volatility	Annual average Europe Brent Spot Price FOB (Dollars per Barrel) - Coefficient of variation	U.S. Energy Information Administration, http://www.eia.gov
Oil & Gas Rents	log of rents from oil + gas as share of GDP.. Rents are defined as the price minus the average extraction costs. The data are described in Hamilton and Clemens (1999).	World Bank's adjusted net savings dataset.