

DOES GREATER TRANSPARENCY REDUCE FINANCIAL VOLATILITY?

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Abstract

While market uncertainty and volatility are widely believed related and synonymous, the volatility impact of uncertainty when caused by market *opacity* is less understood. We develop a model where market opacity drives agents to seek non-price of information to uncover values. One such information is the bid-ask volume, reflecting the demand vs. supply strength. But using this information is inherently unstable and leads to financial cascades. Our Monte Carlo simulations reveal instances of such cascades. We test the opacity-volatility relation for 23 OECD and emerging markets for 2000-2009, using World Economics Forum transparency data, finding strong support for the model.

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

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DOES GREATER TRANSPARENCY REDUCE FINANCIAL VOLATILITY AND CASCADES?

1 Introduction

It is well understood that market uncertainty is closely tied to financial volatility. In fact, uncertainty is commonly measured by various metrics of volatility³. But this implies that there may be a potential circularity where the direction of causality between uncertainty and volatility is unclear. In this paper, we are interested in uncertainties that can be distinguished from volatility but are still capable of generating large market volatility and potential cascades. One such uncertainty is one based on market *opacity*. This may take the form of financial opacity in an institutional sense, or short-run opacities that are associated with financial crisis. An example of the latter is the credit freeze of late 2008 which stemmed from banks not being able to determine which ones carried toxic assets, while examples of the former are widely discussed in international policy circles. For example, in analyzing the 1994-95 Mexican crisis and of the 1997-98 emerging market crisis the IMF blames “a lack of transparency” (IMF, 2001), which it defines 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).⁴⁵

What is the mechanism that links opacity driven uncertainties to destabilizing financial cascades and large financial volatility? The micro literature on herds and cascades is not entirely suitable for the type of opacity driven market uncertainty. For example, two of the most prominent strands in this literature,

³The most common measure of uncertainty is the volatility of macro level stock market returns (Bloom, 2009; Baker and Bloom, 2012); alternative and closely correlated measures of uncertainty are the volatility of firm-level stock returns (Campbell et al., 2001; Bloom et al., 2007; and Gilchrist et al, 2009), forecasting dispersions (Bachman et al, 2010; Popescu and Smets, 2010; and Arslan et al, 2011), volatility of output and productivity (Bloom et al. (2011), Bachman and Bayer (2011), and Kehrig (2010), the volatility of income and consumption (Blundell et al (2008); and Meghir and Pistaferri (2004), exchange rate volatility (Baker and Bloom, 2011; Serven, 1998) and also the volatility of bond yields (Baker and Bloom, 2011; Beber and Brandt, 2009)

⁴The idea of searching for uncertainties that are "exogenous" to volatility is not entirely new (Baker and Bloom, 2012).

⁵For a discussion of the relation between transparency and international investor behavior see Gelos and Wei (2002)

the sequential Bayesian learning processes⁶, or the bank runs⁷, both assume an environment of information asymmetry, but one in which it is still possible for uninformed investors to *observe* (directly or indirectly) the behavior of informed investors which they can then mimic. Moreover, there is an assumption that prices generally reflect fundamentals. For example, in discussing the relation between information asymmetry and opacity, Flannery, et. al. (2013) state, "if investors in general cannot value a firm's assets very accurately, perhaps insiders or specialized traders can." (p. 59).

But if broad macroeconomic uncertainty is the result of financial opacity two types of limitations arise. First, if investors are atomistic information about who is an informed investors may be hard to know and furthermore the atomistic market participants cannot directly observe the behavior of such informed investors. Second, in opaque environments prices produce a poor signal of underlying value⁸. In these cases opacity leads to uncertainty, not only about the information (i.e., what is true underlying value of a security), but also about *who* possesses that information. For example, by mid 2008, investors gradually began to realize that the market value of "toxic" assets did indicate the quality of the underlying loans (uncertainty in price mechanism). Against this background the credit freeze of late 2008 was triggered since no single bank knew the size of other bank's holdings of such assets (uncertainty about who was informed). Thus, both types of opacity prevailed in the market.

In these circumstances agents (investors, traders, etc.) may look for additional signals to uncover underlying value. A natural candidate is in the quantity space. For example, agents may consider the ratio of the *ask* volume to the *bid* volume in addition to prices. If prices are efficient and fully reflect all the information this ratio should be entirely correlated with the price movement and conveys no new information. But if prices are opaque, such indicators may be

⁶This represented for example by earlier papers on sequential Bayesian learning models of Bikhchandani et al. (1992), Bikhchandani and Sharma (2000) or Lee (1993) where individuals follow others observed behavior regardless of their own private information. Chari and Kehoe (2004) develop a continuous trading feature which produces herd behavior due to the trapping of information beyond the optimal time where investment decisions are made (timing is endogenous) This is a generalization of Lee (1998) in which a fixed cost of trading is what leads investors to stop trading after a point, again causing information to be traps. For an excellent but somewhat dated survey see Devenow and Welch (1996).

⁷This literature which began with the famous paper by Diamond and Dybvig (1983) and was followed by many others, is based on negative payoff externalities to (Devenow and Welch 1996).

⁸For example, in discussing the Asian economic crisis, Furman and Stiglitz (1998) point out, "In developing countries, the absence and thinness of markets exacerbates the information problem; fewer securities are subject to the 'price discovery' function of markets, and the accuracy with which those functions are performed is less." (ibid, p. 69)

contain additional information and can be seen by the market as a signal reflecting the behavior of (unknown) informed agents (who atomistic agents cannot directly identify). But once the quantity signal is allowed, a key and distinguishing feature of this type of signal is that unlike the automatic equilibrating mechanism of prices, decisions made on the basis of the quantity signal—i.e. selling when most are selling (*ask* to *bid* volume ratio is high) and buying when most are buying (*ask* to *bid* volume ratio is low)—lead to positive feedbacks and therefore have the potential to be destabilizing. As such, we have the ingredients of what may be called a "macro-herd" effect that could potentially generate cascades⁹. 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).

We develop a simple model of the such a macro effect in a market where prices are not only endogenous (i.e., subject to supply and demand for securities) but follow a Geometric Brownian Motion *and* at the same time incorporate opacity (about the accuracy of the price mechanism) that is built into the model. Then running Monte Carlo simulations for 100 periods with up to 20,000 runs, we try to uncover the mechanisms that lead to financial cascades. Finally we empirically estimate the implications of the model for a number of economies over time (see below).

Our model must take account of additional complexities: If uncertainty driven by opacity can lead to higher volatility due to this "macro herd" effect, then more transparent markets should be more stable and less subject to such an effect. 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 in-

⁹Aggarwal and Wu (2006) make the connection between opacity and herd behavior: They show that when markets are less transparent, such as the OTC market in the US, stock market manipulation occurs and during such periods 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 these traders act as herds, free riding on others' information and exacerbating volatility in the process. Here, however, we do not know who the informed investors are and also price itself is very noisy signal.

stitutional investors who use aggressive, short-term trading strategies which in turn can raise the volatility of the firm’s stock price.

The simulated results of the model are consistent with *both* of these outcomes: For a wide range of a parameter values an “inverted-U” effect arises in which improvements in transparency, when transparency is low (markets are opaque) actually increase volatility, but beyond a certain point, further 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. Finally and crucially our model also predicts that, over time, episodes of stable behavior are interrupted by massive spikes in buy or sell behavior indicated by very large ask to bid volume ratios.

To empirically test our results, we need detailed stock market data, a suitable 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 discussed 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 Carlo simulations; Section 4 presents the empirical evidence; and section 5 provides the concluding remarks.

2 Model

In light of the above background, there are two types of information in the market, the equity price and what may be a proxy for the equity price momentum,

the ask-to-bid volume ratio reflecting the underlying sell-to-buy ratio or strength of supply and demand for securities. As was discussed in the Introduction, to the extent that the price mechanism is opaque or, at times of greatly inaccurate, the ask-to-bid volume may contain useful information. However, even under full information the ask-to-bid volume ratio may contain useful information when agents are *heterogenous*.¹⁰ This is because heterogeneity among agents leads to *different* interpretation of any given price. Thus, additional information, such a volume of trade, becomes useful and is taken into account in trading decisions. 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. This assumes that the underlying information is public, as in the case of this paper in which both price and ask-to-bid volume are public, so that differences among agents is due to their *interpretation* of the public information. As such our approach falls within the genre of behavioral models such Boswijk et. al. (2007), rather than models in which agent heterogeneity is due to information asymmetry where agents belong to informed and uninformed groups (for a survey see Hommes 2006). Finally, in defense of agent heterogeneity, one might add that to generate market trading in which 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. For example, Wang (1994) points out that investors trade among themselves simply because they are different.

In short both opacity and agent heterogeneity render trade volume information useful. In this paper both conditions exist. As such, both the price and the ask-to-bid volume will be inputs of agents' decision. However, the weight of the two factors is influenced by the degree to which the price discovery mechanism is opaque. This provides us with the way in which uncertainty about the price mechanism enters agents' decisions. It is crucial to note that unlike the self equilibrating nature of the price mechanism, the mechanism by which ask-to-bid volume enters is potentially unstable.

The behavior of agents is governed by their "reservation" values of the equity price and of ask-to-bid volume ratio. The "reservation" price reflects traders' subjective valuation of the fundamental value of an equity above and below which trading decisions are made¹¹. Agents are distributed randomly by a con-

¹⁰The focus of our model is the *action* of trading. Thus we 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.

¹¹This reservation value itself may reflect the agents' subjective expectation of the market

tinuum of these reservation prices and reservation ask-to-bid volume ratios such that the observed price or sell to buy ratio may exceed one agent’s reservation value but be less than another agent’s reservation thus creating a market of both sellers and buyers. A final decision by an agent of whether to sell or buy will be based on the weighted average of *both* price and quantity considerations, where the weight on the quantity factor (the bid to ask volume ratio) increases with the degree of price opacity. Even though agents’ initial valuation may be random and subjective, it turns out that with full information, markets converge and are stable. But in the presence of price opacities cascades may emerge. We treat each channel separately, as if agents focused on one channel at a time. We then focus on the combined decision based on both price and quantity channels.

2.1 The Price Channel

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 by their unique reservation price P_r with a probability density function, $g(p_r)$ at any given time. Now consider an observed price P_t at time t . Given this realization, agents will then be divided into two types; those with a reservation price less than or equal to the observed price, $P_r \leq P_t$ and those with a reservation price exceeding P_t , that is $P_r > P_t$. (To simplify exposition, we denote r to indicate both the reservation values and 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 the subjective valuation of the innate value of the equity is still larger than its market price, leading these agents to engage in further purchase of equities.¹²

Let $U(P_t - P_r)$ represent the utility of agent r with $U' > 0$ and $U(0) = 0$. Given a price observation, P_t for type I agents, if $P_t > P_r$ the resulting non-

strength or momentum regarding a stock.

¹²For simplicity we are not concerned here with agent’s wealth constrains. Thus, margin buying is in effect allowed. Further to keep the model simple, we are not modeling short sales.

negative utility $U^I(P_t - P_r) > 0$ can be maximized if agents *sell* their position and realized P_t . For type II investors, if $P_r > P_t$ a positive utility $U^{II}(P_r - P_t) > 0$ is maximized if agents engage in (additional) purchase of stocks. In short,

$$U^{*I} = \text{Max}[U^I(P_t - P_r)|_{P_t > P_r}, U^I(0)|_{P_t \leq P_r}] \implies$$

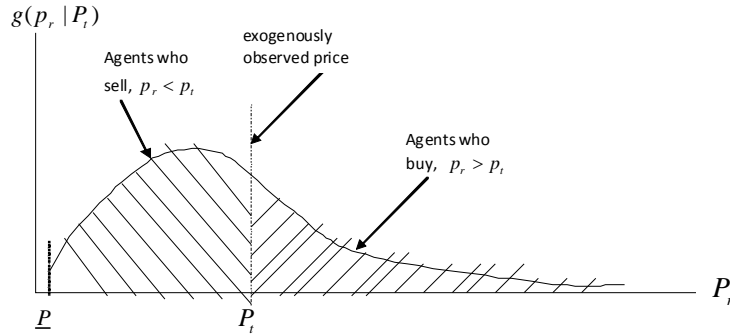
Sell when $P_t > P_r$; otherwise do nothing

$$U^{*II} = \text{Max}[U^{II}(P_r - P_t)|_{P_r > P_t}, U^{II}(0)|_{P_r \leq P_t}] \implies$$

Buy when $P_t < P_r$; otherwise do nothing

Given the random distribution of agents 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' Reservation Prices



To better understand suppose price P_t increases. This would result in two effects: First, the mass of the distribution increases to the left of P_t and decreases to its right. 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. We call this, the “*probability-mass transfer effect*”. However, as stated previously, agents may update their reservation price, given the new information

price information. 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, may reconsider this decision because observing the new (higher) price, increases their evaluation of the fundamental value and thus their reservation price P_r . This affects the probability mass of agents to the left of P_t (and also by implication the probability mass of those to the right of P_t). In probability terms, the two states of 1 (initial price state) and 2 (new price state) can be compared in terms of the shift of the probability mass:

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

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 at any given time and for any observed P_t , there is a $g(P_t)$ fraction of agents whose reservation price is $P_r \leq P_t$ and $1 - g(P_t)$ fraction whose reservation price is $P_r > P_t$. 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 change. Later, when we choose a Pareto distribution to represent g , this aspect will be reflected by dynamic considerations of the parameter of Pareto, depending on whether prices rise or fall from a previous period. But this does not affect the *contemporaneous* integrity of Pareto at any moment in time.

The above results can be written as follows:

$$m_{t+1}(P_t) |_{price\ channel} = \int_{\underline{P}}^{P_t} g(P_r | P_t) dP_r \quad (1)$$

$$n_{t+1}(P_t) |_{price\ channel} = \int_{P_t}^{\infty} g(P_r | P_t) dP_r \quad (2)$$

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:

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

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

2.2 The Quantity Channel

Consider the quantity channel alone (as stated the two channels we be later combined). The methodology is similar to the price channel, but the outcome is distinct due a positive feedback mechanism that eventually feeds the potential market instability. Agents are again also assumed to be randomly distributed now along a new variable value η_r with probability $f(\eta_r)$. The variable η_r denotes both agents *reservation value* of the ask-to-bid (or sell to buy). For any observed value of η_t at time t agents are distinguished by two types; those with a reservation ratio less than or equal to the observed ratio,

$$\eta_r < \eta_t$$

and those with a reservation ratio exceeding the observed ratio,

$$\eta_r > \eta_t$$

Upon observing η_t , agents of the first type see the number of bids (sellers) relative to asks (buyers) is "too" high, relative to their subjective value, η_r . Thus, these agents will engage in selling their position. Unique to this channel,

such an action *reinforces* next period value of η_t hence the source of potential instability. Agents of the second type consider the current observed number of bids to asks η_t not high enough relative to their subjective value, η_r . Thus they engage in buying the stocks, which again reducing the next period value of η_t . As in 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:

$$V^{*I} = \text{Max}[V^I(\eta_t - \eta_r)|_{\eta_t > \eta_r}, V^I(0)|_{\eta_t < \eta_r}] \implies$$

Sell if $\eta_t > \eta_r$; otherwise do nothing

$$V^{*II} = \text{Max}[V^{II}(\eta_r - \eta_t)|_{\eta_r > \eta_t}, V^{II}(0)|_{\eta_r < \eta_t}] \implies$$

Buy if $\eta_t < \eta_r$; otherwise do nothing

The figure that depicts this scenario is analogous to figure 1 with $f(\eta_r|\eta_t)$ replacing $g(\cdot)$ on vertical axis and η_r replacing P_r on the horizontal axis. The figure will not be repeated here. As in price space, any exogenous increase in η_t will increase the number of agents of type I and reduce those of type II as the probability mass moves from left of η_t to the right of η_t . This is the “probability mass transfer effect” as before. Because of this, a higher observed value of η_t this period increases next period’s observed ratio, η_{t+1} creating a vicious cycle that is at the heart of financial cascade mechanism in this paper. Because action here is predicated upon inferring the action of others via the quantity space, one might call this channel a “macro 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, we 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. Thus, the herd mechanism is unambiguously destabilizing.

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

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

$$n_{t+1}(\eta_t) |_{quantity\ channel} = \int_{\eta_t}^{\infty} f(\eta_r|\eta_t) d\eta_r \quad (5)$$

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., $\eta > 0$). It follows that,

$$\eta_{t+1} |_{quantity\ channel} = \frac{m_{t+1}}{n_{t+1}} = \frac{\int_{\underline{\eta}}^{\eta_t} f(\eta_r) d\eta_r}{\int_{\eta_t}^{\infty} f(\eta_r) d\eta_r} \quad (6)$$

2.3 Combining Channels

In practice agents take both channels of information into account. Suppose a trade decision takes into account the quantity channel with a weight θ ($\theta \in [0, 1]$) and the price channel with a weight factor of $1 - \theta$ (More about θ later). Define a grand utility function, W , such that:

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

Since in general agents may be bullish (bearish) under the price channel and bearish (bullish) under the quantity channel a trade decision under one channel is not necessarily consistent with a trade decision under another channel (V

and U are not maximized under a *consistent* action set). In this case, the importance of a channel (size of θ), and the distance measures, $|P_t - P_r|$ and $|\eta_t - \eta_r|$, determine the ultimate decision of each investor.¹³ 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 price P_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:

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

One can think of Θ and as an indication of the weight that market puts on prices, and $1 - \Theta$ as indication of the weight that market puts on investor behavior. Appendix 1 develops a framework that shows how Θ is related to the opacity of the markets. Intuitively, since in non-transparent states of the market, prices are not as informative, reliance on other investor's behavior (the quantity channel) becomes more prominent as a conveyor 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 adjustments

A key component of the model is the role of the price adjustments. We assume that prices are subject to two forces; (1) the usual Geometrical Brownian Motion

¹³To 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 decision.

as indicated by the Wiener process and (2) a price response function to η_t 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 $G' < 0$) 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:

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

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

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:

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

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

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. 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, indicated by extreme value distributions, can be used to describe 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,

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

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:

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

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

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

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

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

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

$$m_{t+1} |_{quantity} = F(\eta_r < \eta_t) = 1 - (\underline{\eta}/\eta_t)^{\gamma(\eta_{t+1}/\eta_t)} \quad (16)$$

$$n_{t+1} |_{quantity} = prob(\eta_r \geq \eta_t) = (\underline{\eta}/\eta_t)^{\gamma(\eta_{t+1}/\eta_t)} \quad (17)$$

$$\eta_{t+1} |_{quantity} = \frac{F(\eta_r < \eta_t)}{prob(\eta_r \geq \eta_t)} = \frac{1 - (\underline{\eta}/\eta_t)^{\gamma(\eta_{t+1}/\eta_t)}}{(\underline{\eta}/\eta_t)^{\gamma(\eta_{t+1}/\eta_t)}} \quad (18)$$

Thus equation (7) can be written as:

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

2.5 The Price Response

A focus on how prices are determined in the aggregate is often missing in the micro literature, such as the herd literature. In this paper, prices are both endogenous and possibly opaque, with the latter also tied to aggregate market uncertainties. We assume a form of “excess demand function” that specifies the dynamic nature of market clearing mechanism. We assume a constant elasticity form for this function, as follows:

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

where α is a random variable,

$$\alpha \sim N(\alpha_o, \sigma_\alpha^2) \quad (21)$$

and where,

$$\sigma_a = m \cdot \Theta \Rightarrow \Theta = (1/m)\sigma_a \quad (22)$$

with m as a constant parameter. To explain, there is an opacity in the efficiency of the price response mechanism which is what leads to a financial cascade. The micro foundation for this linkage is established in Appendix 1. This becomes

clearer if we view (22) in its equivalent form $\Theta = \sigma_\alpha/m$. 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 can examine how the system evolves. To do this, we develop the following simulation:

3 Monte Carlo Simulation

The simulation revolves around randomizing two stochastic processes: the price adjustment process via the Wiener process and the macro-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:

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

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 self-buy ratio tied to preference update (ν) and changes in self-buy ratio	δ_o	0.9
Weight on herd versus price channel (tied to α)	?	0.05-0.80
Drift of stock price on daily basis	μ	0.0003
Lower bound threshold value of Pareto distribution for self-buy ratio	$\underline{\eta}$	0.1
Lower bound threshold value of Pareto distribution for stock price	\underline{P}	0.1
Factor tying ? to α	M	2
Initial price and self-buy ratio for the dynamics		1

3.1 Simulation Outcome

Simulation results are presented in the three panels of figure 2. 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 (the quantity dimension 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 the macro quasi-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 entails.

To check these result we compare the quantity and the price volatility over 100 periods for the three cases. This is reported in panels of figures 3 and 4. Figure 3 depicts rather well the inherent "bubbles" associated with the quantity channel and financial cascades. This is seen by the dramatic, abrupt and short-lived spikes in the quantity volatility (i.e., the ask to bid ratio η), interrupting otherwise smooth and stable stochasticity of η . By contrast, the price behavior over time from figure 4, exhibits no dramatic spikes, but instead shows a higher average volatility. Finally, varying the reservation update parameter, ν , does not seem to make much of a difference in this qualitative description.¹⁴

¹⁴However, 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 2-Transparency and Volatility (ν indicates the speed of reservation value updates)

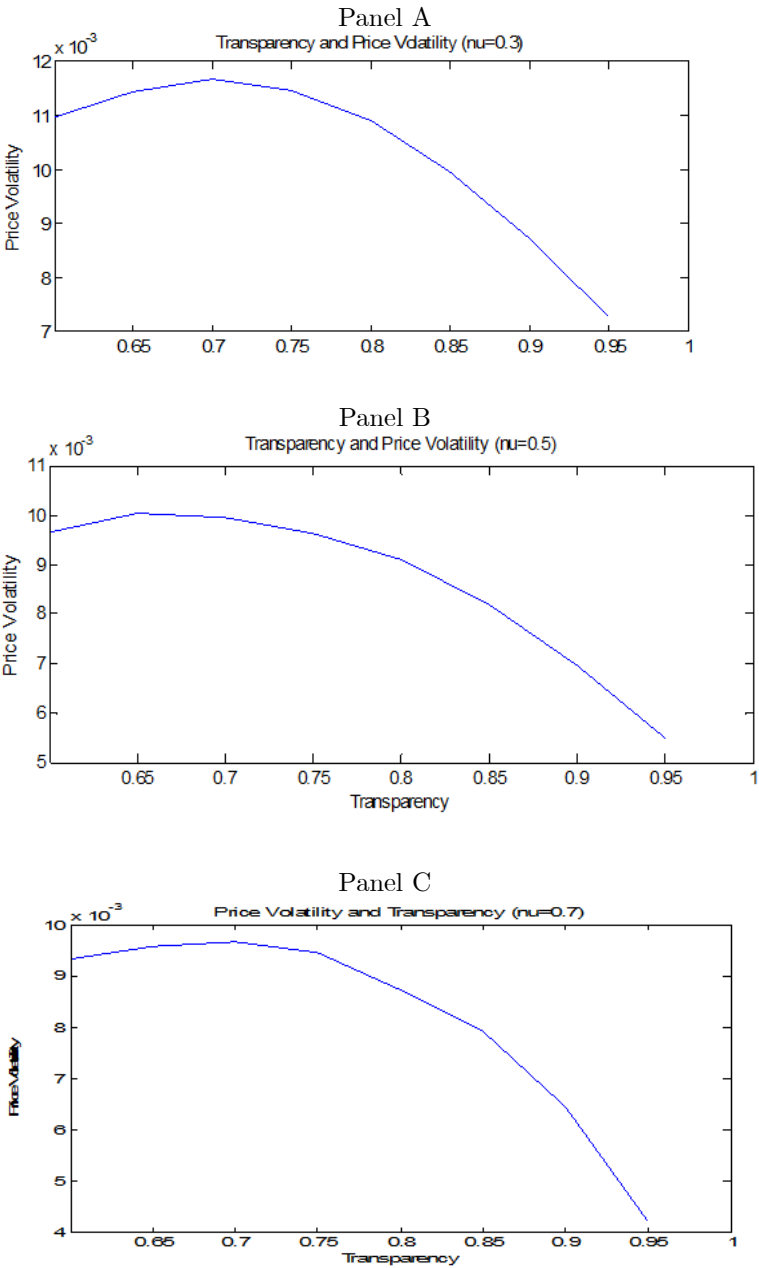
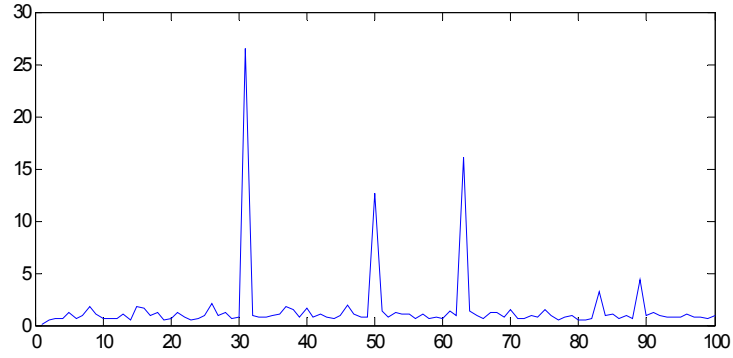


Figure 3- Quantity Volatility over Time

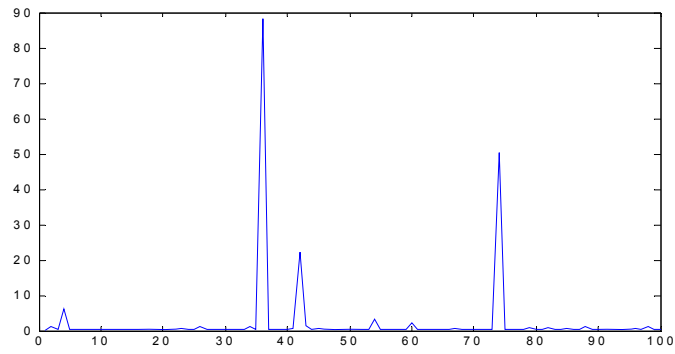
Panel A

speed of adjustment $\nu = .30$



Panel B

speed of adjustment $\nu = .50$



Panel C

speed of adjustment $\nu = .70$

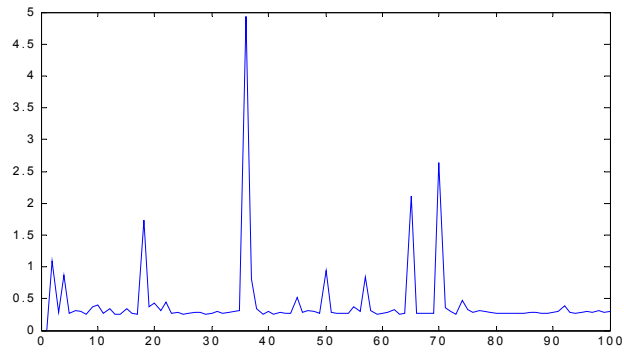
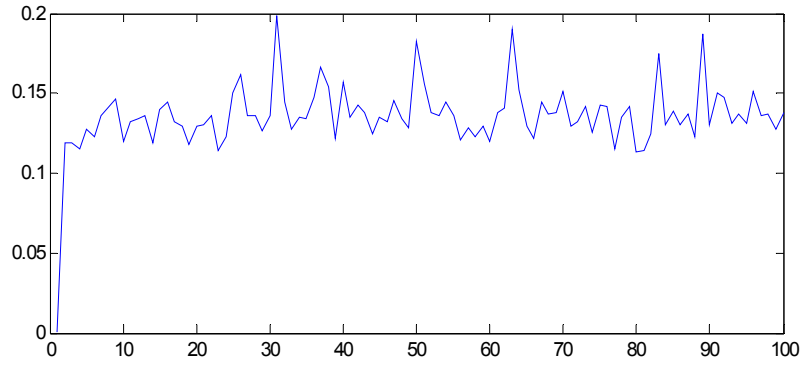


Figure 4- Price Volatility over Time

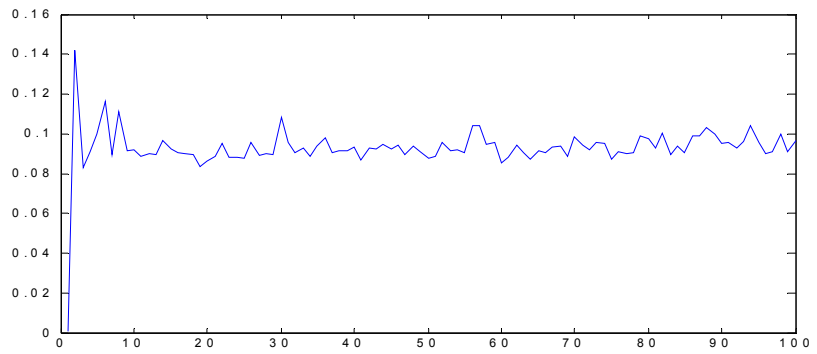
Panel A

speed of adjustment $\nu = .30$



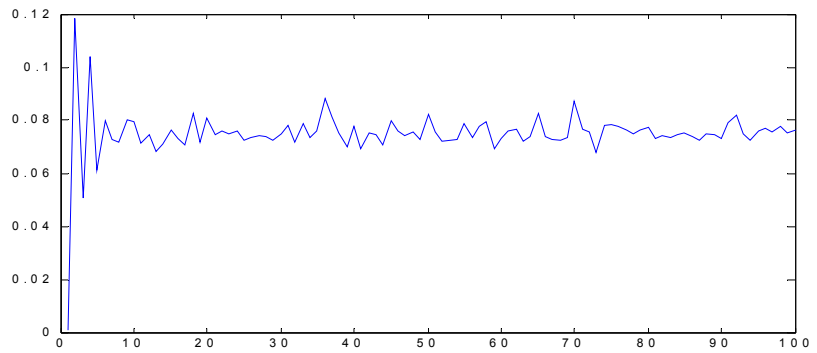
Panel B

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*.¹⁵

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.¹⁶ 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 re-

¹⁵Both 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.

¹⁶See Appendix for a full definition of the variables and data sources.

gressions.¹⁷ 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 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. Figure 6 confirms this.

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.

¹⁷We 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.)

5 Summary and conclusion

We have developed a randomized analytical model of financial cascades based on market opacity. We have numerically simulated this model, using a Monte Carlo method and discovered that at very limited levels transparency, (high opacity) an initial increase in transparency may actually initially increase volatility, but will eventually reduce volatility.

We have examined this theoretical finding for the period 2000 to 2009. 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. Our results are strongly supportive of the theory that volatility may initially rise with greater transparency when transparency is very low, 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
Bélgium	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 in dex value

	Strength of Audit			Transp. of Gov't Policy		
	OLS (1)	FE (2)	RE (3)	OLS (4)	FE (5)	RE (6)
Transparency	1113.0*** (271.37)	1030.4*** (260.59)	153.07* (85.594)	226.39** (98.166)	247.29** (101.79)	163.11 (105.92)
Transparency2	-109.56*** (26.889)	-100.92*** (25.648)	-19.004** (8.2095)	-28.054** (11.142)	-31.151*** (11.770)	-18.096 (11.584)
Trade	-0.6704*** (0.1932)	-0.6775*** (0.1994)	-0.5493 (0.3903)	-0.5147*** (0.1902)	-0.4722** (0.1935)	-0.6120 (0.4758)
Turnover Ratio	-0.8890*** (0.2821)	-1.0032*** (0.3046)	-0.4135 (0.5140)	-0.9591*** (0.2926)	-1.1235*** (0.3231)	-0.3077 (0.5744)
Stocks Traded	0.3141** (0.1321)	0.3006** (0.1402)	0.3743 (0.3604)	0.3578*** (0.1328)	0.3812** (0.1528)	0.2983 (0.3808)
Log(GDP per Capita)	-24.071** (11.156)	-25.378** (11.087)	-7.7455 (18.017)	-26.238** (11.088)	-24.196** (10.346)	-22.415 (18.571)
Libor 3-month (mean)	12.972 (9.7236)	8.7598 (17.450)	7.9225 (6.2445)	12.194 (10.403)	0.9532 (17.387)	8.5835 (6.8507)
Financial Crisis Dummy (2008=1)	117.88 (79.906)	79.726 (88.042)	121.04** (55.338)	131.69 (85.166)	75.215 (90.267)	117.92** (53.168)
Constant	-2348.3*** (599.94)	-2082.0*** (585.11)	-67.631 (301.19)	-21.614 (228.03)	33.372 (239.26)	-24.738 (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 Feller 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 Feller 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*** (138.16)	507.01*** (133.66)	139.02** (63.979)	116.06** (48.825)	125.11** (50.901)	83.007 (51.067)
Transparency2	-53.822*** (13.665)	-49.483*** (13.140)	-14.687** (6.5451)	-14.220** (5.5704)	-15.544*** (5.8679)	-9.2255* (5.5826)
Trade	-0.3240*** (0.0982)	-0.3280*** (0.1014)	-0.2852 (0.1958)	-0.2505*** (0.0950)	-0.2329** (0.0977)	-0.3054 (0.2321)
Turnover Ratio	-0.3964*** (0.1483)	-0.4519*** (0.1558)	-0.1956 (0.2657)	-0.4360*** (0.1565)	-0.5147*** (0.1659)	-0.1256 (0.3157)
Stocks Traded	0.1518** (0.0659)	0.1398** (0.0705)	0.1939 (0.1810)	0.1715** (0.0678)	0.1774** (0.0775)	0.1485 (0.1982)
Log(GDP per Capita)	-15.173** (5.8712)	-15.774*** (5.7657)	-11.011 (8.9990)	-16.457*** (5.7292)	-15.481*** (5.3687)	-14.921 (9.3952)
Libor 3-month (mean)	7.5480 (4.8018)	6.6292 (8.5238)	5.0799 (3.7613)	7.4206 (5.1297)	2.9766 (8.3576)	5.7081 (4.0795)
Financial Crisis Dummy (2008=1)	68.473 (43.307)	48.331 (46.868)	70.075** (33.096)	74.874 (46.081)	46.430 (47.923)	68.495** (32.046)
Constant	-1138.1*** (306.37)	-1008.0*** (300.01)	-155.00 (143.21)	3.6885 (114.60)	30.342 (120.26)	12.900 (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 (1)	FE (2)	RE (3)	OLS (4)	FE (5)	RE (6)
Transparency	2320.9*** (582.66)	2150.1*** (558.33)	491.03** (234.57)	494.86** (203.10)	534.90** (213.13)	370.07* (208.43)
Transparency2	-226.46*** (57.656)	-208.54*** (54.886)	-53.321** (22.865)	-60.407*** (23.115)	-66.369*** (24.651)	-41.320* (23.172)
Trade	-1.4018*** (0.4178)	-1.4174*** (0.4311)	-1.2195 (0.8366)	-1.0733*** (0.4042)	-0.9906** (0.4112)	-1.3061 (1.0083)
Turnover Ratio	-1.7585*** (0.6074)	-1.9925*** (0.6501)	-0.9129 (1.3234)	-1.8892*** (0.6337)	-2.2153*** (0.6895)	-0.6561 (1.5308)
Stocks Traded	0.6936** (0.2808)	0.6550** (0.3001)	0.8638 (0.8915)	0.7682*** (0.2913)	0.8105** (0.3348)	0.6774 (0.9543)
Log(GDP per Capita)	-73.063*** (25.549)	-75.663*** (25.176)	-45.288 (40.693)	-73.933*** (25.171)	-69.855*** (23.758)	-64.757 (42.011)
Libor 3-month (mean)	29.588 (20.439)	22.788 (37.000)	19.657 (14.260)	29.545 (21.800)	7.9009 (36.755)	22.851 (15.384)
Financial Crisis Dummy (2008=1)	286.06 (178.83)	205.77 (195.54)	293.94** (132.60)	311.87 (190.24)	198.38 (200.06)	286.64** (128.16)
Constant	-4764.7*** (1282.4)	-4219.5*** (1246.0)	-395.49 (629.42)	50.999 (476.43)	162.5 (506.14)	45.730 (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

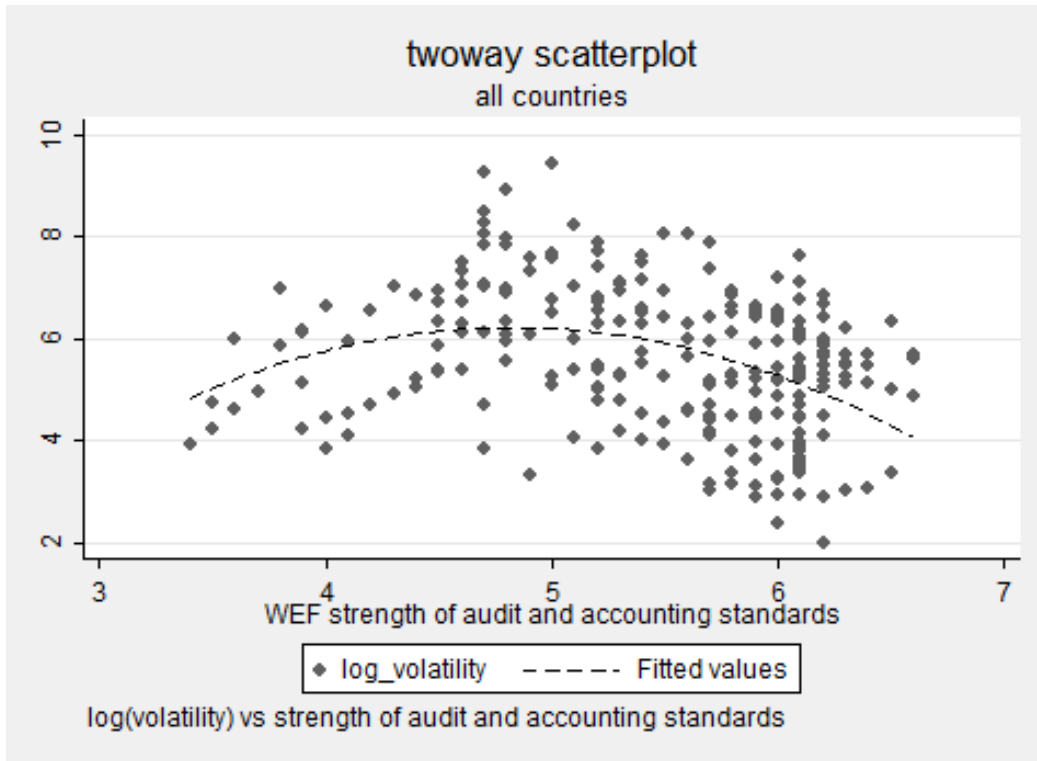
Table 7. Transparency & Volatility: Week with Largest Market Drop

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*** (1256.4)	4649.1*** (1226.2)	1294.2** (586.30)	1153.0** (454.37)	1241.7*** (474.28)	896.39* (485.30)
Transparency2	-492.13*** (123.78)	-454.44*** (120.15)	-137.65** (62.758)	-139.37*** (52.388)	-152.30*** (55.353)	-97.495* (54.688)
Trade	-3.0565*** (0.9116)	-3.0907*** (0.9397)	-2.6114 (1.6462)	-2.4734*** (0.9183)	-2.3026** (0.9329)	-2.8471 (2.0247)
Turnover Ratio	-4.2296*** (1.4280)	-4.7161*** (1.5139)	-3.2628 (2.6278)	-4.8094*** (1.5126)	-5.5128*** (1.6266)	-2.8749 (3.0104)
Stocks Traded	1.5862** (0.6874)	1.5068** (0.7184)	2.2992 (1.7954)	1.8076** (0.7227)	1.9038** (0.8001)	2.0834 (1.9747)
Log(GDP per Capita)	-109.92* (61.114)	-115.70* (61.363)	-89.899 (94.279)	-125.01** (55.584)	-116.59** (53.906)	-144.94 (98.323)
Libor 3-month (mean)	63.557 (39.013)	49.690 (70.015)	41.016* (24.354)	63.677 (41.898)	16.855 (70.413)	45.980* (27.831)
Financial Crisis Dummy (2008=1)	816.41* (431.52)	653.16 (460.18)	847.64** (358.24)	877.20* (458.98)	638.24 (470.28)	834.55** (348.71)
Constant	-10607.1*** (2768.3)	-9470.9*** (2736.7)	-1458.8 (1190.8)	-363.66 (1018.8)	-134.40 (1072.0)	-47.763 (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 6: Scatter Plot of the Impact of Accounting and Audit Standards on Price Volatility



Appendix 1: Market Opacity and Herds

Although we have focused on the macro dimensions of cascades and herds, it is possible to develop a micro foundation even if this is not in the conventional micro herd behavior of the Bayesian variety. The purpose of this exercise is to establish the micro foundation for the linkage between price opacity and Θ as was discussed in equation (22). 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 k th 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 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 $k-1$ st 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 k th 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 k th 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	$S_2 T$	$B_2 T$	$S_2 S_1 O$	$B_2 B_1 O$
individual 3	$S_3 T$	$B_3 T$	$S_3 S_2 O$	$B_3 B_2 O$
...				
individual k	$S_k T$	$B_k T$	$S_k S_{k-1} O$	$B_k B_{k-1} O$

We are then interested in the general probability of herd formation, $prob(S_k|S_{k-1}|S_{k-2}|\dots|S_1)$ or $prob(B_k|B_{k-1}|B_{k-2}|\dots|B_1)$ 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,

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

where the first term on 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)¹⁸. Thus, $prob(S_2|S_1|O) = 1$. Continuing this procedure for period 3 we have:

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

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 .

¹⁸In Bikhchandani and Sharma and Bikhchandani and Hirshleifer, this probability is initially less than 1, since the private information 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.

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

$$\begin{aligned} \text{prob}(\text{herd formation at } k) &= \text{prob}(S_k|S_{k-1}|S_{k-2}|\dots|S_1) = \dots \\ &= 1 - \rho(1 - \pi^{n-1}) \end{aligned} \quad (\text{A3})$$

It is now clear that,

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

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.mortgage-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.