NOISE TRADERS AND SHORT-SELLING TROUBLED FIRMS
(preprint)

ABSTRACT

Purpose: This paper examines the efficacy of recent policy initiatives taken by the U.S. Securities and Exchange Commission (SEC) banning naked 'short-selling' of specific financial stocks (SEC, 2008 a,b,c). The study also considers the merits of reinstating 'uptick rule' 10a-1, which prohibits short-selling securities on a downtick.

Design/methodology: We study theoretical implications of short-selling in a simple state-claim model, reflecting varying amounts of short interest in a representative firm and noise trading in the market. Price discovery depends on the proportion of noise trading compared to rational short-selling. Our empirical analysis focuses on price volatility under short-selling constraints employing simple regressions, EGARCH analysis and simulated price behavior under a hypothetical uptick rule.

Findings: The EGARCH results suggest short-selling constraints had non-uniform impacts on the persistence and leverage-effects associated with price volatility. The corresponding price simulations indicate a hypothetical uptick rule might have helped stabilize price behavior in some cases, depending on the nature of the stochastic process and whether or not quantity constraints on short selling were binding.

Originality/value: Our theoretical arguments and empirical findings suggest a "focused approach" to market regulation would be a more efficient means of discouraging trend chasing without compromising 'informed trading' ─that is to say, safeguarding price discovery and market liquidity without impeding arbitrage or confounding probability beliefs regarding firm survival. These conclusions are largely in accord with recent policy analysis and proposals outlined in Avgouleas (2009).

Keywords: Noise traders; short-selling; EGARCH

JEL Classification: G-13, G-14, G15

Categorization of paper: Research Paper

1. INTRODUCTION

Short-sellers participate in financial markets by first borrowing and then selling securities. The aim is to repurchase the security at a lower price in the near future, thereby making a profit if the asset's price decreases between the time of sale and purchase. Thus regulatory constraints on short-selling transactions can take various forms. Of present concern are strict prohibitions that ban short-sales altogether (sales constraints), and conditional prohibitions that rule-out short-selling in situations where price declines are persistent (price constraints). We treat these two types of regulation as heuristic representations of the recent ban on short-sales and the potential tick-test governing short-selling, i.e. rule 10a-1 which prohibits short-selling of a security in a "down" market.[1]

Clearly, short-selling stocks can have adverse impacts on the valuation of troubled firms, and perhaps even the likelihood of their survival. However, the implications of regulating short-selling remain open to question in situations where rational and non-rational agents take 'short interest' positions in troubled firms (as measured by the total amount of shares sold short and yet to be repurchased to close out the positions). Presumably high levels of short interest reflect beliefs that share values will fall further. The extent to which these beliefs reflect fundamental information is a matter of present concern.

[1] The U.S. uptick rule (10a-1) was adopted in 1938 following an inquiry into the effects of concentrated short-selling during the market break of 1937. The SEC eliminated the rule on July 6, 2007, noting that price test restrictions "modestly reduce liquidity and do not appear necessary to prevent market manipulation" (SEC, 2007).

Theoretical analysis of short-sales constraints begins with Miller's (1977) stock-pricing hypothesis and extensions by Harrison and Kreps (1978), Jarrow (1980), Diamond and Verrecchia (1987), Allen et al. (1993), Morris (1996), and Hong and Stein (2003). This literature considers how constraints on short-selling affect the propensity to trade and the ability for prices to adjust to good or bad news (O'Hara, 1994). If agents are free to short-sell a stock then the stock's price will tend to reflect relatively pessimistic beliefs of the firms' prospects (Diamond and Verrecchia, 1987).[2] This begs the following questions: i) are short-sellers acting as rational agents; and ii) are the policy implications of imposing a moratorium on short-selling substantively different from imposing conditional price restrictions?

Short-sellers may include passive investors, arbitragers and noise-traders. Collectively these agents share common (pessimistic) beliefs regarding the firms' future prospects. These beliefs are rational to the extent they reflect available information concerning fundamental valuations; that is, the net present value of future cash flows, appropriately discounted for risk considerations. On the contrary, non-rational valuations are based on some less exacting basis. For example, non-rational agents may apply trading strategies that are independent or correlated, such as "reading tea leafs" or "trading with the crowd." In either case the asset price may still approximate fundamental value as reviewed in Shleifer (2000).

Firstly, non-rational trading strategies that are independent could cancel-out, permitting rational investors to determine a price consistent with fundamental value. Secondly, non-rational trading strategies that are correlated tend to create profitable investment opportunities. In this case, it

[2] See Avgouleas (2009) esp. pp. 21-26 for a comprehensive survey of empirical literature identifying various forms of efficiency benefits from short-selling, e.g. Bris, Goetzmann and Zhu (2007).

has been famously argued that market-clearing prices remain efficient signals of fundamental value so long as rational agents take positions against-the-crowd and hold these positions for sufficiently long periods of time (Freidman, 1953; Fama, 1965). Non-rational traders who persist in selling the underpriced security eventually lose money to better-informed traders, along with their influence over price.

The present paper considers regulatory policy governing short-selling when noise trading is persistent. Policy implications are drawn from a simple state-claim model reflecting varying amounts of short interest in the firm and noise trading in the stock market. The study maintains noise traders are key in applying market regulations since these agents increasingly sell a troubled asset the lower its price becomes, motivating "smart money to chase dumb money." In particular, if rational agents (arbitrageurs) hold short-interest then selective use of price limits would benefit the market relative to more intrusive market regulations, e.g. imposing a blanket ban on short-selling or market-wide uptick rules, which are more likely to impede arbitrage or confound probability beliefs. The argument for "focused regulation" is largely in accord with recent policy recommendations offered by Avgouleas (2009) in terms of discouraging non-rational trading while improving price discovery and market liquidity. Some empirical evidence in support of the limited regulation approach is offered from the recent market experience.

2. STATE-CONTINGENT ASSET PRICING

An efficient securities market allows free-exchange of state-claims over the residual cash flows of a firm. In this environment, risk is priced into securities as information emerges concerning the firm's prospects. However, if noise-traders dominate the market then prices become noisy signals of intrinsic value. Under these conditions the relatively strong hypothesis of market efficiency is subject to doubt, as noise-traders take short positions in the firm. This behavior potentially distorts fundamental valuation and the ability to attract capital resources. To put this argument in concrete terms we consider a simple state-claim model of asset pricing.

Following Arrow (1971) let corporate shares (the risky asset) represent state-contingent claims on the firm's cash flows. Thus, a share of stock is desired by an individual because of the chance it will provide a payoff contingent on some future state-of-the-world (SOW). A standard treatment of the problem is given in Hirsheliefer and Riley (2002). Let $\boldsymbol{Z}_{\boldsymbol{as}}$ denote the income from asset a = 1,2 in SOW s= 1,2. Asset prices are denoted by $\boldsymbol{P}_1^{\boldsymbol{A}}$ and $\boldsymbol{P}_{\boldsymbol{2}}^{\boldsymbol{A}}$ and their quantities by $\boldsymbol{q}_1$ and $\boldsymbol{q}_2$. The (representative) investor's budget constraint in asset units is given by

1. $$\boldsymbol{W} = \boldsymbol{P}_1^{\boldsymbol{A}}\boldsymbol{q}_1 + \boldsymbol{P}_2^{\boldsymbol{A}}\boldsymbol{q}_2 .$$

If the individual is endowed with asset quantities $\bar{\boldsymbol{q}}_1$ and $\bar{\boldsymbol{q}}_2$ and wealth $\overline{\boldsymbol{W}}$ then the individual's state-claims $(\boldsymbol{c_1}, \boldsymbol{c_2})$ reflect payoffs from the two-asset portfolio

2. $$\begin{pmatrix} \boldsymbol{c}_1 \\ \boldsymbol{c}_2 \end{pmatrix} = \boldsymbol{k}_1 \frac{\overline{\boldsymbol{W}}}{\boldsymbol{P}_1^{\boldsymbol{A}}} \begin{pmatrix} \boldsymbol{Z}_{11} \\ \boldsymbol{Z}_{12} \end{pmatrix} + \boldsymbol{k}_2 \frac{\overline{\boldsymbol{W}}}{\boldsymbol{P}_2^{\boldsymbol{A}}} \begin{pmatrix} \boldsymbol{Z}_{21} \\ \boldsymbol{Z}_{22} \end{pmatrix}$$

where $\boldsymbol{k_i}, \boldsymbol{i} = 1,2$ denote wealth-shares in assets 1 and 2 with $\boldsymbol{k_1} + \boldsymbol{k_2} = \mathbf{1}.$ Complete markets in tradable assets exist if the market system allows trading in all elementary state-claims. Let

π_1, π_2 denote subjective probability beliefs of an investor over two states of the world. The investor's portfolio choice problem is then given by

3. $\max_{k_1, k_2} EU = \pi_1 \upsilon(c_1) + \pi_2 \upsilon(c_2)$ subject to

4. $c_1 = k_1 \dfrac{\overline{W}}{P_1^A} Z_{11} + k_2 \dfrac{\overline{W}}{P_2^A} Z_{21} \qquad (= q_1 Z_{11} + q_2 Z_{21})$

5. $c_2 = k_1 \dfrac{\overline{W}}{P_1^A} Z_{12} + k_2 \dfrac{\overline{W}}{P_2^A} Z_{22} \qquad (= q_1 Z_{12} + q_2 Z_{22})$

6. $k_1 + k_2 = 1.$

In this set-up optimal risk bearing requires the investor equalize the expected marginal utility per dollar held (invested) in each asset (*fundamental theorem of risk bearing)*:

7. $\dfrac{P_2^A}{P_1^A} = \dfrac{\pi_1 \upsilon'(c_1) Z_{21} + \pi_2 \upsilon'(c_2) Z_{22}}{\pi_1 \upsilon'(c_1) Z_{11} + \pi_2 \upsilon'(c_2) Z_{12}}.$

For expositional purposes assume asset 2 (risky asset) has payoffs $(Z_{21}, Z_{22}) = (4, 0)$ and price P_2^A, while asset 1 (risk-free numeraire) has payoffs $(Z_{11}, Z_{12}) = (1, 1)$ and price P_1^A. Under these assumptions the *fundamental theorem of risk bearing* is represented by

8. $\dfrac{P_2^A}{P_1^A} = \left[\dfrac{4}{1+\phi}\right], \qquad \phi = \dfrac{\pi_2 \upsilon'(c_2)}{\pi_1 \upsilon'(c_1)} \qquad \begin{array}{l} c_1 = q_1 + 4q_2 \\ c_2 = q_1. \end{array}$

Increasing the odds of failure, i.e. $\uparrow(\pi_2/\pi_1)$ or $\downarrow(\pi_1/\pi_2)$, implies a higher ϕ-value consistent with a lower share price P_2^A relative to the risk-free asset price P_1^A. Essentially increased risk of a zero-payoff is priced into the asset, depending on the shareholder's marginal rate of substitution (MRS) between state-contingent income claims. We use a numerical example to consider the influence of information on investors taking long or short positions in the stock.

Numerical example. The investor's choice problem is examined numerically assuming exponential preferences over state-claims $\upsilon(c_i) = 1 - e^{-Ac_i}$, where A denotes constant absolute risk aversion (CARA). In this case the optimal risk-bearing condition becomes

9. $$\frac{P_2^A}{P_1^A} = \frac{4}{1 + (\pi_2/\pi_1)e^{A(c_1 - c_2)}} = \frac{4}{1 + (\pi_2/\pi_1)e^{A4q_2}}.$$

Taking the natural log and rearranging terms yields the following investment decision rule

10. $$q_2 = \frac{1}{4A}\ln\left\{\left(\frac{\pi_1}{\pi_2}\right)\left(\frac{4P_1^A}{P_2^A} - 1\right)\right\}.$$

Whether the agent takes a long or short position in the risky asset ($q_2 > 0$ or $q_2 < 0$) depends on the agent's probability beliefs and risk aversion. A risk-free trading portfolio implies asset demand $q_2 = 0$, corresponding to the "certainty state-claims." Long positions are taken based on probability beliefs $\pi_2 < \pi_1$, otherwise short positions are taken. By shorting the agent assumes a liability in state-of-the-world 1, i.e. $|q_2 Z_{21}| = 4|q_2|$. Increased CARA reduces the size of the positions taken (either long or short), as the individual becomes less responsive to given changes in the odds of failure. Further consideration of this argument is given in a market-clearing model allowing for rational and non-rational investment behavior. The market equilibrium takes the form of a 'noisy rational expectations equilibrium' to the extent noise trading is active.[3]

Noise traders, information and market-clearing. As Black (1986) put it, noise traders are agents who "trade on noise rather than information." Accordingly noise traders (denoted by *N*) follow a 'non-Bayesian' approach in forming expectations; that is, they systematically violate Bayes' Rule in predicting the firm's prospects for survival. For example, noise traders would place market orders to sell shares at lower prices, ignoring information regarding firm fundamentals. For reasons of tractability suppose noise traders are risk neutral and apply the following ad-hoc decision rule in taking short positions

$$11. \qquad \boldsymbol{q}_3^N = \boldsymbol{\beta} \ln\left\{\frac{4}{\boldsymbol{P}_2^A}\right\}, \qquad \boldsymbol{where} \quad \boldsymbol{\beta} > 0.$$

Clearly, no rational investor (Bayesian agent) would follow this "dumb-money" trading strategy. Instead we assume rational investors (denoted by superscript R) follow a Bayesian process in forming their beliefs. The decision rules governing investment are defined by (10), depending on risk preferences $(\boldsymbol{A}_1^R, \boldsymbol{A}_2^R)$ and probability beliefs $(\pi_1/\pi_2)_{R1}, (\pi_1/\pi_2)_{R2}$

$$12. \qquad \boldsymbol{q}_1^R = \frac{1}{4\boldsymbol{A}_1^R} \ln\left\{\left(\frac{\pi_1}{\pi_2}\right)_{R1}\left(\frac{4}{\boldsymbol{P}_2^A} - 1\right)\right\}, \qquad \boldsymbol{q}_2^R = \frac{1}{4\boldsymbol{A}_2^R} \ln\left\{\left(\frac{\pi_1}{\pi_2}\right)_{R2}\left(\frac{4}{\boldsymbol{P}_2^A} - 1\right)\right\}.$$

[3] See O'Hara (1994) for a discussion of the 'noisy rational expectations framework,' esp. ch. 6.

Referring to Table (1), assume rational investors have common prior beliefs $\pi_1 = \pi_2 = .5$. To allow for divergent beliefs each SOW is interpreted as having a given likelihood of occurring, depending on a noisy signal of the firm's prospects (positive or negative). Assume the signal is conditioned by the degree of noise trading in the market as characterized in the likelihood matrix. If the true SOW is non-failure then a positive signal corresponds to a 60% chance of non-failure; a negative signal corresponds to a 40% chance of failure. Alternatively if the true SOW is failure, then a positive signal implies a 20% chance of non-failure while a negative signal implies an 80% chance of failure. Applying Bayes theorem, the positive signal results in a posterior distribution (.75, .25), while a negative signal results in the posterior distribution (.33, .67). The implications for market-clearing are considered below in the presence of noise traders.

<Table 1>

Market-clearing with noise traders. In the absence of monopoly power over the stock price we can assume agents treat price as parametric and submit excess demand schedules for the stock to a 'Walrasian auctioneer.'[4] The market-clearing price balances the volume of long and short positions, thereby reflecting informed and uninformed probability beliefs, risk aversion, and the degree of noise trading in the market, α

13. $$n_1 q_1^R + \alpha(n_2 q_2^R) + (1-\alpha) n_3 q_3^N = 0.$$

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[4] Note that the total stock of the risky asset is treated as being zero. An alternative would be to treat the aggregate supply of the risky asset as a random variable. However, as noted by Hirshleifer and Riley (2002), this approach is not easily justifiable in many contexts (see Section 7.3)

Table (2) summarizes relationships among the various model parameters. If Bayesian investors have common priors $\pi_1 = \pi_2 = .5.$ then they only take long positions in the market. Consequently, the short side of the market consists entirely of noise traders, with the market-clearing price decreasing in the degree of noise and the degree of risk aversion. The bottom portion of the Table summarizes the same relationships assuming some agents incorporate bad news in revising their prior beliefs. In this informative case short-sellers consist of rational and non-rational agents, and the market-clearing price decreases further as rational short-sellers become better-informed of firm fundamentals.

<Table 2>

What emerges from the above analysis is a noisy rational expectations hypothesis about the nature of short-selling behavior and stock price adjustments. From a policy perspective this relationship can be regulated by imposing constraints on either short-sellers themselves (a ban), or on short-sale transaction prices (a price test). An empirical look at these policy measures follows based on the SEC's recent ban on short-selling financial stocks.

3. EMPIRICAL ANALYSIS

The SEC ban on 'naked' short-selling was motivated by the potential to "cause sudden and excessive fluctuations of security prices, thereby impairing the operation of fair and orderly markets" (SEC, 2008c).[5] Thus, on July 15, 2008 the SEC announced regulations banning naked short selling in Fannie Mae (FNM), Freddie Mac (FRE) and 17 other financial stocks (effective

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[5] 'Naked' short selling occurs when sellers do not even borrow the underlying shares before selling them and then look to cover their positions sometime after the sale.

July 21 to August 12). The regulations were expanded on September 18, prohibiting *all* short selling in an additional 780 financial stocks (effective September 19 to October 8). Finally on July 27, 2009 the emergency rule banning the practice of naked short selling was made permanent.[6] To study the price-effects of the ban we use simple regressions, EGARCH analysis (Nelson, 1991), and simulated price behavior under a hypothetical uptick rule. We focus on the 25 most shorted stocks on the NYSE and NYSE ACRA for which short-selling was prohibited on July 15, 2008. Presumably increased short-interest reflected beliefs that stock values would fall further.

We take an initial look at the empirical relationship between short interest and stock price behavior using OLS regressions around the time of the July 15th announcement. Table (3) identifies the initial sample of firms and their symbols, the amounts of short interest and stock prices for the months of July and August, and the percentage of the stock shorted. We are interested in the coefficient of correlation between short interest and stock prices ($\boldsymbol{r} = \sqrt{\boldsymbol{R}^2}$), and the OLS parameter estimates for short-interest. Thus to avoid measurement bias with autocorrelations or spuriously inflated correlations we regress percentage changes in short-interest (%ΔS) on percentage changes in stock prices (%ΔP). The bottom of Table (3) reports regression results for three sample periods: a 6-week period overlapping the announcement (7/01/2008 to 8/16/2008), and a two-week and four-week period before and after the announcement (7/01/2008 to 7/16/2008 and 7/16/2008 to 8/16/2008).[7]

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[6] Importantly, the permanent ruling requires that brokers must promptly buy or borrow the underlying security to deliver on a short sale.

[7] The SEC "emergency action" temporarily banned investors from short-selling 799 financial firms (and a few others closely related to the financial sector). This expanded regulation followed the bankruptcy of Lehman Bros. and financial disclosures by American Intl. Group. The policy actions also ushered in the debate over the "too big to fail" argument for financial regulation. See Helwege (2009) for an insightful discussion of these events.

<Table 3>

The OLS estimates of the short-interest parameter (%ΔS = -1.19, -0.68) indicate the inverse relationship between short interest and stock returns weakened following the regulatory announcement. Correspondingly the correlation value between the two variables ($r = \sqrt{R^2}$) dropped from 0.66 to 0.32. The results also indicate that daily stock returns tended to increase after the ban was imposed, as shown by the upward shift in the constant term (from -0.04 to 0.15) and increase in statistical significance (t statistics from -1.36 to 3.22).[8] Nonetheless, the average return to an equally weighted portfolio of the most shorted stocks was approximately -6% over the two-month period (July-August), with a standard deviation of 27%.[9]

The continuation of 'falling security prices' and 'excessive price fluctuations' motivated the SEC to ban *all* short selling of nearly 800 financial stocks, effective September 19, 2008. We examine how the expanded ban affected daily stock returns (R_t) and their volatility for our working sample using EGARCH models. EGARCH models measure the log of the conditional variance of stock returns ($\log\sigma_t^2$) as a weighted average of the long-run variance (ϖ), the log of the variance for the previous period (the GARCH term, $\log\sigma_{t-1}^2$), and any new information revealed through the previous error in predicting mean returns (the ARCH term containing ε_{t-1}). We estimate the following EGARCH (1,1) model for each firm in our working sample:

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[8] This finding is in accord with observations reported by Boehmer, Jones and Zhang (2008), which find an initial bounce in share prices on NYSE-listed stocks subject to the early ban. A similar bounce was reported by FSA (2009) comparing returns on FTSE-traded stocks.

[9] That heavily shorted stocks tend to exhibit negative returns is well-documented in previous studies, e.g. Desai et al. (2002).

14. $\boldsymbol{R_t = c + \varepsilon_t}$

15. $$\log \boldsymbol{\sigma}_t^2 = \boldsymbol{\varpi} + \boldsymbol{\beta} \log \boldsymbol{\sigma}_{t-1}^2 + \boldsymbol{\gamma} \frac{\boldsymbol{\varepsilon}_{t-1}}{\boldsymbol{\sigma}_{t-1}} + \boldsymbol{\alpha} \frac{|\boldsymbol{\varepsilon}_{t-1}|}{\boldsymbol{\sigma}_{t-1}}$$

where $\boldsymbol{\varpi}, \boldsymbol{\beta}, \boldsymbol{\gamma}$ and $\boldsymbol{\alpha}$ are constant parameters. The EGARCH process ensures the conditional variance of stock returns is positive without ad-hoc restrictions on the model parameters.

We assume market participants identify "good news" as a signal of increased stock returns (positive shocks, $\boldsymbol{\varepsilon_{t-1} > 0}$) and "bad news" as a signal of lower returns (negative shocks, $\boldsymbol{\varepsilon_{t-1} < 0}$). Thus, a previous shock of good news contributes to current volatility with $(\boldsymbol{\alpha} + \boldsymbol{\gamma})|\boldsymbol{\varepsilon}_{t-1}|/\boldsymbol{\sigma}_{t-1}$, and a previous shock of bad news with $(\boldsymbol{\alpha} - \boldsymbol{\gamma})|\boldsymbol{\varepsilon}_{t-1}|/\boldsymbol{\sigma}_{t-1}$. When $\boldsymbol{\gamma = 0}$ it follows positive and negative shocks have symmetric effects on volatility; and when $\boldsymbol{\gamma < 0}$ negative shocks generate more volatility than positive shocks, so bad news is said to have a "leverage effect." The "persistence" of volatility following a news shock is captured by $\boldsymbol{\beta \to 1}$: as beta tends to unity volatility becomes more persistent, indicating slower mean-reversion.

We study how the expanded ban affected volatility persistence and leverage by comparing EGARCH parameter estimates for two periods: a 125-day period before September 19th and a 125-day period after October 18th. Table (4) reports summary statistics for the cross-sectional time series of closing prices ($\boldsymbol{p}$) and daily stock returns ($\boldsymbol{R}$).[10] The coefficient of variation gives a simple indication of the degree of randomness, combining a measure of central tendency

[10] Relative to the initial sample of firms our working sample excludes Washington Mutual, Lehman Bros, Citigroup, Natl. City Corp., and the Wachovia Group. Statistics for all of the remaining firms are reported in Table (A) in the appendix.

(sample mean, μ) with a measure dispersion (sample standard deviation, σ), i.e. CV=σ/μ. The CV statistics for closing prices and the %-change in closing prices suggests there was an increase in price dispersion after the expanded ban on short selling was imposed.

<Table 4>

Table (5) reports the Maximum Likelihood estimates for the EGARCH models. The statistically significant parameter estimates are denoted by asterisks (95% level * and 99% level **).

<Table 5>

Tables (6a) and (6b) identify firms by changes in their volatility persistence and leverage-effect parameters (β and γ). We consider cases where persistence or leverage remained about the same after introduction of the wide-spread ban, and cases where persistence or leverage changed. We differentiate among the latter category according to whether persistence or leverage became stronger or weaker.

<Tables 6a and 6b>

Columns 1 and 2 in Table (6a) list firms for which volatility persistence was roughly unchanged after the wide-spread ban was imposed. Non-persistence is relatively rare, limited to AMD, FNM, and FRE. Strong persistence is more common, as seen in AIG, BAC, CP, CDE, F, GM, USB and WFC.[11] Columns 3 and 4 list firms which experienced change in volatility persistence. Persistence became stronger for DIS, MU, RF and S, and became weaker for BBT, COF, ABK, CNB, and SNV. Accordingly, the expanded ban may have dampened volatility persistence in five out of twenty-one cases studied.

Columns 1 and 2 in Table (6b) list firms whose leverage-effects seem unchanged by the wide-spread ban: five firms had no leverage-effects (AMD, CNB, COF, F, and GM); and four firms had strong leverage-effects (CP, RF, USB and WFC). Column 3 lists firms where the leverage-effects became stronger (ABK, CDE, and MU), implying bad news began having a greater impact on volatility than good news. Column 4 lists firms where leverage-effects became weaker (AIG, BAC, BBT, and SNV), with bad news having less impact on price volatility.[12] Finally, column 5 reports several cases where good news generated more volatility than bad news: Fannie Mae (FNM) in both periods, Freddy Mac (FRE) in the second period, and Disney and MBIA Inc. in the first period.

We complete our empirical analysis of short selling policy with a simulation of price adjustments under a hypothetical 'uptick rule.' An uptick rule, such as *10-a1,* is akin to a regulated price in executing short sales. The argument for its use rests on promoting more efficient pricing of securities under speculative attack. On the NYSE short sales would only be transacted on a plus tick (uptick) or a 'zero-plus tick,' i.e. a price higher than the last price, or a price equal to the last price but higher than the last different price. For example, a short sale could be executed at $4 if

[11] The observation of no significant changes in volatility persistence coincides with observations reported by the FSA (2009) in comparing returns for the FTSE 350 over pre- and post-ban periods.
[12] This observation is consistent with the argument that unencumbered short-selling allows markets to adjust faster to 'bad news,' e.g. see Bai, Chang and Wang (2006).

the previous price sequence (beginning with the oldest price) is 3.875, 3.875, and 4. However if the previous price sequence is 4.125, 4.125, and 4, then a trade at $4 would be on a 'zero-minus tick' and not allowed.

We simulate the affect of imposing price tests on four firms drawn from our working sample: BAC, FNM, FRE and USB. We assume the security prices follow firm-specific stochastic processes subject to the suspension of dividend payments to shareholders:

$$\textbf{16.} \qquad \frac{\Delta P}{P} = \mu\Delta t + \sigma\varepsilon\sqrt{\Delta t},$$

where $\Delta P/P$ is the proportional return provided by the stock in time interval Δt ; $\mu\Delta t$ is the expected value of the return; and $\sigma\varepsilon\sqrt{\Delta t}$ is the stochastic component of the return. We assume short-selling in the underlying stock constitutes one-fifth of trading activity, implying the uptick rule applies in 20-percent of the simulations. Random 'news shocks' are introduced using Normally- and Cauchy-distributed ε -values, [13] in conjunction with firm-specific estimates for drift and volatility (μ and σ) derived from the EGARCH analysis (i.e. the parameter sets $c, \varpi, \alpha, \beta, \gamma$).[14] The simulation period covers 44 days of stock trading.

[13] Cauchy distributions look similar to Normal distributions, but with much heavier tails. Thus, when studying hypothesis tests that assume normality, the Cauchy distribution is a good indicator of how sensitive the tests are to so-called "heavy-tail departures from Normality."

[14] We compute epsilon values at each tick under Normal and Cauchy distributions by "mixing" the initial sigma from the EGARCH with pseudo-randomness generated through a 'Mersenne Twister' (MT19937). The resulting Normally-distributed or Cauchy-distributed epsilon is then applied in obtaining an epsilon for the next tick.

Figures (1a-1d) illustrate differences in simulated prices with and without an uptick rule under the Normal distribution. Figures (2a-2d) illustrate simulation results under the Cauchy distribution. We consider price performance for two sample-periods corresponding to the EGARCH parameter sets. The simulated prices are drawn using quotes to the nearest $1/8 if the price is above $3 and $1/16 if the price is at or below $3 (standard tick sizes on US stock exchanges). Because we are interested in price differentials with and without the uptick rule (price spreads) we illustrate all simulations beginning with a common spread value of zero. Thus as the trials progress positive values imply the regulated price exceeded the free market price, creating a positive spread. Negative values imply the uptick rule was ineffective at supporting the simulated price.

Figure (1a) shows results for Bank of America (BAC) prices under the Normal distribution. The solid line (BACN1) reflects EGARCH parameters from the first observation period (before the wide-spread ban), and the dotted line (BACN2) from the second observation period (after the ban was introduced). The simulations suggest the uptick rule provides more stable price-support under the second set of BAC parameters. Figures (1b) and (1d) show the same policy impact for Fannie Mae (FNM) and US Bancorp (USB): the uptick rule gives more stable price support under the second set of EGARCH parameters. Conversely, the price simulations for Freddie Mac show the uptick rule giving more stable price-support under the first set of parameters.

<Figures 1a-1d>

Figures (2a-2d) show the performance of the uptick rule under the Cauchy process. Here the price support function behaves more randomly, most likely due to the heavy-tail properties of the Cauchy distribution. Figure (2a) illustrates the case of BAC. Here again the uptick rule provides more certain price support over the second observation period, and Figures (2b) and (2d) again show similar (albeit noisier) policy performance for FNM and USB. Figure (2c) offers a somewhat different policy impact for Freddie Mac (FRE), with prices generally supported in both observation periods, though more randomly.

<Figures 2a-2d>

The various simulations provide some support for the argument that uptick rules can be effective constraints on noise-driven short-selling, potentially contributing to a more rational price discovery process. However, at least two key qualifications stand in the way of offering general conclusions. First, the EGARCH results show firm-specific volatility varies across firms according to persistence and leverage, and the presence or absence of quantity constraints on short-selling. Secondly, our simulation analysis is somewhat simplified in ignoring the potential for dynamic "feedback effects" between price volatility and the degree of short interest in troubled firms. Nonetheless, the results obtained suggest a blanket uptick rule has disparate impacts on price stability, depending on the firm-specific parameters that govern the stochastic process.

4. CONCLUDING REMARKS

On July 27, 2009 the SEC made permanent the order prohibiting the practice of naked short-selling of certain financial stocks. Previously the SEC banned all short-selling of nearly 800 stocks. To help maintain liquidity certain exceptions were made for registered market makers. The SEC has also considered reinstating 'uptick rule' 10a-1, which prohibits short-selling securities on a downtick. These policy measures were taken to moderate "sudden and excessive fluctuations in security prices." In taking these steps regulators noted that "sudden price declines give rise to questions about the underlying financial conditions of an issuer, which in turn can create a crises of confidence without a fundamental underlying basis. This crisis of confidence can impair the liquidity and ultimate viability of an issuer, with potentially broad market consequences" (SEC, 2008c).

Important cost-benefit questions arise in regulating short-selling, since high levels of short interest reflect beliefs that share values will fall further. Whether these beliefs reflect fundamental information is a focal point of the present study. Certainly 'bad news' concerning a troubled firm motivates rational short- and long-sellers to post the same shares at the same time, thus exacerbating negative price pressure. Clearly if agents are free to short-sell then share prices will tend to reflect relatively more pessimistic beliefs of the firms' prospects. Interestingly, a study by the Office of Economic Analysis (OEA) found 'long-sellers' (who sell their own stock) were the primary cause of price drops during the recent high volatility periods in U.S. markets (OEA, 2008).

The observation of falling prices during high volatility periods coincides with the predictions given by our noisy rational expectations model, wherein some agents are rational sellers. Under free-market conditions our model predicts the equilibrium price decreases in the degree of noise trading and investor risk aversion, with rational and non-rational agents taking short positions in troubled firms. Imposing a sales constraint under these conditions results in less-informed beliefs regarding firm fundamentals to the extent 'informed traders' withdraw from the market.[15] Hence, the SEC's exception of registered market-makers was important in terms of ensuring the provision of liquidity to rational arbitrageurs, who otherwise might have withdrawn from shrinking securities markets.

Our empirical analysis of short-selling constraints focuses on price volatility, employing simple regressions, EGARCH analysis and simulated price behavior under a hypothetical uptick rule. The EGARCH results suggest short-selling constraints had non-uniform impacts on the persistence and leverage-effects associated with price volatility. Moreover, the corresponding price simulations indicate a hypothetical uptick rule might have helped stabilize price behavior in some cases, depending on the nature of the stochastic process and whether or not quantity constraints on short selling were binding. Consequently, our findings indicate blanket uptick rules are prone to some degree of failure in supporting stock valuations, given the wide-ranging response to news observed in our sample of troubled firms.

Based on our findings we are inclined to join the chorus of financial economists arguing for a "focused approach" to market regulation. As described here the "focused approach" corresponds

[15] Boehmer, Jones and Zhang (2008) provide empirical evidence that short-sellers tend to be well-informed and trade on fundamentals.

more closely with the SEC's interpretation of a "*security-specific, temporary approach*" as opposed to a *"market-wide, permanent approach"* (SEC, 2009). In these regards our findings support recent policy prescriptions outlined in Avgouleas (2009), which call for selective use of price limits and disclosure of short-selling positions. These policy measures are capable of discouraging trend chasing (herding) without compromising 'informed trading' —that is to say, not impeding arbitrage or confounding probability beliefs regarding firm survival.

En fin, we remind the reader of Milton Friedman's persuasive argument, that non-rational traders who persist in selling a truly underpriced security will eventually lose money to better-informed traders, along with their influence over price. But this assumes better-informed traders are not constrained from participating in markets.

Table 1: Bayesian probability analysis

Likelihood Matrix	Noisy signal			*Joint Pr.*	Noisy signal		*Prior Pr*	*Posterior Pr*	Noisy signal	
	Good	Bad			Good	Bad			Good	Bad
SOW1: Non-failure	0.6	0.4	1.0		0.3	0.2	0.5		0.75	0.33
SOW2: Failure	0.2	0.8	1.0		0.1	0.4	0.5		0.25	0.67
					0.4	0.6	1.0		1.0	1.0

Table 2: Market-clearing relationships

Priors R1: $\pi_1 = \pi_2 = 1/2$ R2: $\pi_1 = \pi_2 = 1/2$		*Rational long traders*	*Rational short traders*	*Short noise traders*	*Market-clearing price*
Degree of noise	*Risk aversion*	q_1^R	q_2^R	q_3^N	P^*
$\alpha = 0.1$	A=0.25	0.0374	0.0337	0.0712	1.96
	A=0.30	0.0377	0.0339	0.0716	1.95
$\alpha = 0.5$	A=0.25	0.2812	0.1406	0.4218	1.72
	A=0.30	0.2953	0.1476	0.4429	1.65
$\alpha = 0.9$	A=0.25	1.1925	0.1190	1.3110	0.93
	A=0.30	2.4150	0.2415	2.6500	0.21
Posteriors R1: $\pi_1 = 1/2; \quad \pi_2 = 1/2$ R2: $\pi_1 = 1/3; \quad \pi_2 = 2/3$					
$\alpha = 0.1$	A=0.25	0.3828	-0.2927	0.0903	1.62
	A=0.30	0.3273	-0.2365	0.0908	1.61
$\alpha = 0.5$	A=0.25	0.5769	-0.0656	0.5113	1.44
	A=0.30	0.5576	-0.0163	0.5413	1.35
$\alpha = 0.9$	A=0.25	1.3716	0.0663	1.4379	0.81
	A=0.30	3.5682	0.2978	3.8661	0.05

Table 3: Short-interest and stock prices on the NYSE July-August, 2008

Firm (symbol)	Short-interest (7/2008)	Short-interest (8/2008)	% stock shorted	Stock Price (7/01/08)	Stock Price (8/29/08)
Washington Mutual, Inc (WM)	338.6m	382.4	22.4%	5.25	4.05
Ford Motor Co. (F)	311.3	320.8	14.7	4.71	4.46
Wachovia Corp (WB)	271.9	269.1	12.5	16.13	15.89
Fannie Mae (FNM)	141.4	182.7	17.0	19.59	6.84
Wells Fargo & Co (WFC)	165.8	176.1	5.3	24.12	30.27
National City Corp (NCC)	161.7	166.1	21.8	4.60	5.04
Freddie Mac (FRE)	118.6	158.5	24.5	16.21	4.51
Citigroup, Inc (C)	149.6	150.3	2.8	17.13	18.99
General Motors Corp. (GM)	143.1	146.2	25.8	11.75	10.00
Bank of America Corp (BAC)	112.8	117.5	2.6	23.81	31.14
Advanced Micro Devices Inc (AMD)	93.4	96.4	15.9	5.65	6.29
Regions Financial Corp. (RF)	90.2	91.4	13.2	11.59	9.27
Ambac Financial Group Inc. (ABK)	83.5	91.0	31.7	1.18	7.16
BB&T Corp. (BBT)	84.8	90.3	16.4	23.97	30.00
American Intl. Group Inc. AIG)	78.7	85.8	3.2	26.73	21.49
Micron Technology Inc. (MU)	85.8	85.2	11.2	5.79	4.24
MBIA Inc. (MBI)	86.1	83.6	30.6	4.28	16.22
Sprint Nextel Corp. (S)	88.5	82.7	3.0	8.83	8.72
U.S. Bancorp (USB)	76.5	79.2	4.6	28.40	31.86
Coer d'Alene Mines Corp. (CDE)	72.8	77.1	14.0	2.81	1.79
Lehman Bros. Holdings Inc. (LEH)	70.6	76.9	11.1	20.96	16.09
Capital One Financial Corp. (COF)	73.7	73.5	19.6	40.14	44.14
The Colonial BancGroup Inc. (CNB)	70.1	72.0	35.6	4.96	6.32
The Walt Disney Co. (DIS)	72.6	71.2	3.8	31.05	32.35
Synovus Financial Corp. (SNV)	65.0	69.7	21.1	9.10	9.20

OLS regression results	**Constant term (t statistic)**	**%ΔS t statistic)**	**R^2 (r)**
7/01/2008 to 8/16/2008	0.0855	-1.6815	0.3976
	(1.7815)	(-3.7234)	(0.6306)
Pre SEC Ban: 7/01/20008 to 7/16/2008	-0.0431	-1.1928	0.43111
	(-1.3556)	(-3.9891)	(0.6565)
	0.1500	-0.6782	0.1025
Post SEC Ban: 7/16/2008 to 8/16/2008	(3.2223)	(-1.5484)	(0.3201)

Table (4): Summary statistics for 2nd event sample

Variable	Sample period	Average Mean	Average Min	Average Max	Average Std. Dev.	CV
Closing prices	Before	17.35	9.85	23.88	3.66	0.21
(P)	After	7.96	3.56	13.86	2.74	0.34
%-change	Before	-0.0043	-0.3899	0.2318	0.0714	-16.50
closing prices	After	-0.0057	-0.3155	0.3099	0.0991	-17.43

Table notes: The summary statistics are averages, calculated over the sample means from the cross sectional time series. The CV statistics are calculated as the ratio of the average standard deviation and the average of the sample means.

Table 5: EGARCH (1, 1) parameter estimates (z-statistics)

	Before introduction of wide-spread ban					*Following introduction of wide-spread ban*				
Firm	c	ω	α	β	γ	c	ω	α	β	γ
(ABK) Amb.	-0.014	-1.533**	0.210	0.676**	0.398**	-0.012	-4.465*	0.465*	-0.020	-0.211
Fin. Grp. Inc.	(-1.411)	(-2.824)	(1.823)	(5.079)	(4.516)	(-1.033)	(-2.366)	(2.125)	(-0.044)	(-1.516)
(AIG) Am.	-0.009**	-0.593*	0.570**	0.961**	-0.150*	-0.020*	-1.005**	0.632**	0.888**	-0.0036
Intl. Grp,Inc.	(-2.645)	(-2.503)	(4.535)	(28.259)	(-1.965)	(-2.318)	(-2.706)	(5.132)	(11.99)	(-0.0476)
(AMD) Adv.	-0.002	-4.399*	0.426	0.389	0.234	-0.001	-3.777	-0.128	0.279	0.096
Mic.Dev.Inc.	(-0.502)	(-2.185)	(1.647)	(1.368)	(1.422)	(-0.220)	(-0.619)	(-0.610)	(0.246)	(0.776)
(BAC) Bank	-0.013**	0.109	0.046	1.010**	-0.304**	-0.0181	-0.739	0.361*	0.899**	-0.129
of Am.Corp.	(-4.882)	(1.175)	(1.034)	(68.57)	(-4.756)	(-1.866)	(-1.680)	(2.119))	(11.32)	(-1.692)
(BBT) BB&T	-0.003	-0.788	0.452	0.932**	-0.200*	0.001	-4.428*	-0.565*	0.143	0.097
Corp.	(-0.847)	(-1.598)	(1.857)	(16.90)	(-1.994)	(0.159)	(-2.041)	(-2.592)	(0.362)	(0.640)
(CDE)Cd'A	-0.007*	-0.048**	-0.125**	0.974**	-0.007	-0.003	-0.022	-0.057	0.988**	-0.120**
Mines	(-2.531)	(-3.244)	(-43.47)	(357.83)	(-0.090	(-0.372)	(-0.189)	(-1.041)	(57.27)	(-2.904)
(CNB) Col.	-0.012**	-0.592*	0.318*	0.933**	0.069	-0.022	-6.892**	0.329*	-0.849**	-0.013
Ban.Grp.Inc.	(-2.326)	(-2.530)	(2.120)	(25.442)	(0.477)	(-1.316)	(-30.240	(2.161)	(-10.20)	(-0.298)
(COF) Cap.	-0.002	-0.971	0.318*	0.885**	-0.120	-0.005	-4.082	0.029	0.165	0.175
One Fin.Corp.	(-0.444)	(-1.385)	(2.365)	(8.346)	(-0.810)	(-0.607)	(-1.122)	(0.111)	(0.218)	(1.115)
(DIS) Walt	0.001	-9.108**	-0.491	0.144	0.350**	-0.004	-0.093	-0.054	0.981**	-0.108
Disney Co.	(0.352)	(-4.837)	(-1.643)	(-0.639)	(2.206)	(-1.070)	(-0.365)	(-0.503)	(36.55)	(-1.264)
(F) Ford	-0.002	-0.950**	0.427*	0.883 **	-0.122	-0.001	-0.902	0.186	0.877**	0.102
Motor Co.	(-0.305)	(-2.489)	(2.531)	(14.424)	(-1.454)	(-0.251)	(-1.639)	(1.639)	(6.811)	(1.246)
(FNM)	-0.009	-3.821**	2.512**	0.347**	1.565**	-0.012	-2.653**	0.370*	0.484**	0.316**
Fannie Mae	(-1.348)	(-9.940	(8.947)	(3.925)	(9.475)	(-1.155)	(-3.150)	(2.000)	(2.891)	(2.411)
(FRE)	-0.009	-3.001*	0.601**	0.435	0.068	-0.049**	-4.391**	1.561**	0.089	1.212**
Freddy Mac	(-0.920)	(-2.421)	(3.127)	(1.701)	(0.526)	(-5.252)	(-10.15)	(7.808)	(0.796)	(5.794)
(GM) Gen.	-0.006	-0.023	-0.088	0.983**	-0.040	-0.017	-1.555*	0.659**	0.766**	-0.112
Motors Corp.	(-1.767)	(-0.368)	(-1.491)	(443.5)	(-0.666)	(-1.908)	(-2.589)	(2.905)	(6.402)	(-1.185)
(MBI) MBIA	-0.005	-8.168**	0.826**	-0.552**	0.298**	-0.006	-9.254**	0.354**	-0.919**	0.062
Inc.	(-0.764)	(-19.82)	(5.234)	(-5.263)	(2.775)	(-0.922)	(-17.56)	(3.610)	(-14.87)	(1.362)
(MU) Micron	-0.002	-9.325**	0.193	-0.506	-0.115	-0.009**	-0065**	-0.095**	0.968**	-0.205**
Tech. Inc.	(-0.386)	(-4.339)	(1.560)	(-1.401)	(-1.587)	(-9.317)	(-32.14)	(-28.81)	(2486)	(-5.201)
(RF) Reg. Fin.	-0.012**	0.051**	-0.108**	-0.989**	-0.139**	-0.015	-0.402	0.207	0.949**	-0.163**
Corp.	(-161.1)	(86677)	(-32.9)	(-68.4)	(-47.7)	(-1.633)	(-1.415)	(1.537)	(23.64)	(-2.991)
(S) Sprint	0.0001	-7.169**	0.614**	–0.0193	0.325**	0.002	-0.350	0.137	0.954**	-0.133
Nextel Corp.	(0.437)	(-3.933)	(3.192)	(-0.068)	(3.547)	(0.293)	(-1.251)	(0.942)	(24.30)	(-1.599)
(SNV) Syn.	-0.005*	-0.0131	-0.024	0.991**	-0.114*	-0.006	-7.562**	-0.293	-0.554	-0.155
Fin. Corp.	(-2.092)	(-0.173)	(-0.335)	(86.87)	(-2.031)	(-0.795)	(-3.692)	(-1.436)	(-1.386)	(-1.089)
(USB)	-0.005**	0.114	-0.053	1.005**	-0.242**	-0.015*	-0.032	0.009	0.992**	-0.206*
US Bancorp	(-16.80)	(0.436)	(0.372)	(45.81)	(-5.691)	(-2.548)	(-0.213)	(0.106)	(53.90)	(-2.343)
(WFC)Wells	-0.018**	0.009	-0.062	0.988**	-0.291**	-0.008*	0.083	0.163**	1.022**	-0.249**
Fargo & Co.	(-2.744)	(0.123)	(-0.840)	(53.33)	(-3.097)	(-2.414)	(0.437)	(2.643)	(44.61)	(-7.291)

Table notes: The statistical significance levels of the beta parameters * 95% level, ** 99% level.

Tables 6a: Persistence of volatility before and after expanded ban

Non-existent	*Remained strong*	*Became strong*	*Became weak*	*Other*
Advanced Micro Devices Inc (AMD)	American Intl. Group Inc. (AIG)	The Walt Disney Co. (DIS)	BB&T Corp. (BBT)	MBIA Inc. (MBI)
Fannie Mae (FNM)	Bank of America Corp. (BAC)	Micron Tech. Inc. (MU)	Capital One Fin. Corp. (COF)	
Freddie Mac (FRE)	Canadian Pacific Rail. Ltd. (CP)	Regions Financial Corp. (RF)	Ambac Financial Group Inc. (ABK)	
	Coer d'Alene Mines Corp. (CDE)	Sprint Nextel Corp. (S)	The Colonial Banc Group Inc. (CNB)	
	Ford Motor Co. (F)		Synovus Financial Corp. (SNV)	
	General Motors Corp. (GM)			
	U.S. Bancorp (USB)			
	Wells Fargo & Co (WFC)			

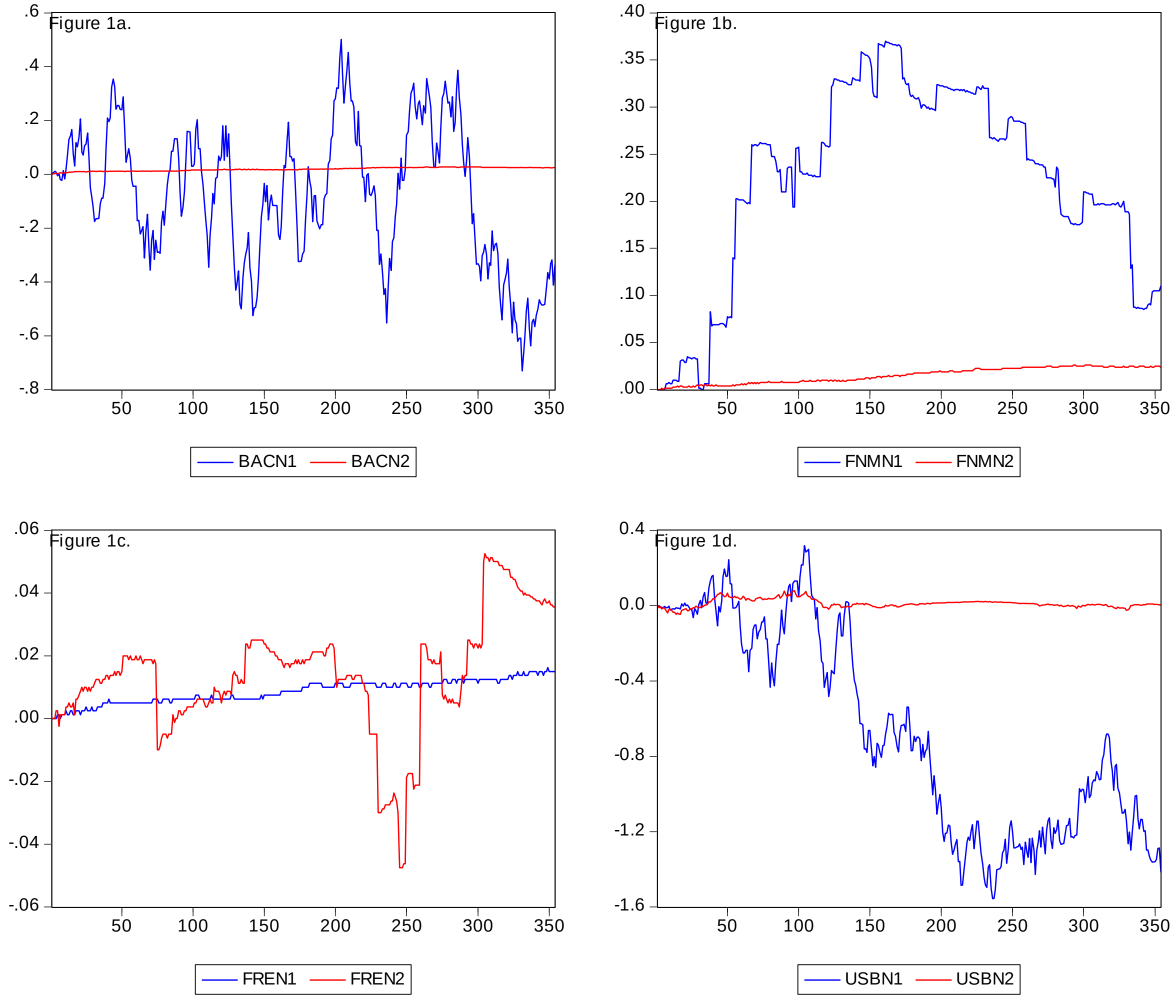
Table 6b: Leverage effect before and after expanded ban

Non-existent	*Remained strong*	*Became strong*	*Became weak*	*Other*
Advanced Micro Devices Inc (AMD)	(CP)	Ambac Financial Group Inc. (ABK)	American Intl. Group Inc. (AIG)	MBIA Inc. (MBI)
The Colonial Banc Group Inc. (CNB)	Regions Financial Corp. (RF)	Coer d'Alene Mines Corp. (CDE)	Bank of America Corp. (BAC)	The Walt Disney Co. (DIS)
Capital One Fin. Corp. (COF)	U.S. Bancorp (USB)	Micron Tech. Inc. (MU)	BB&T Corp. (BBT)	Fannie Mae (FNM)
Ford Motor Co. (F)	Wells Fargo & Co (WFC)		Synovus Financial Corp. (SNV)	Freddie Mac (FRE)
General Motors Corp. (GM)				
Sprint Nextel Corp. (S)				

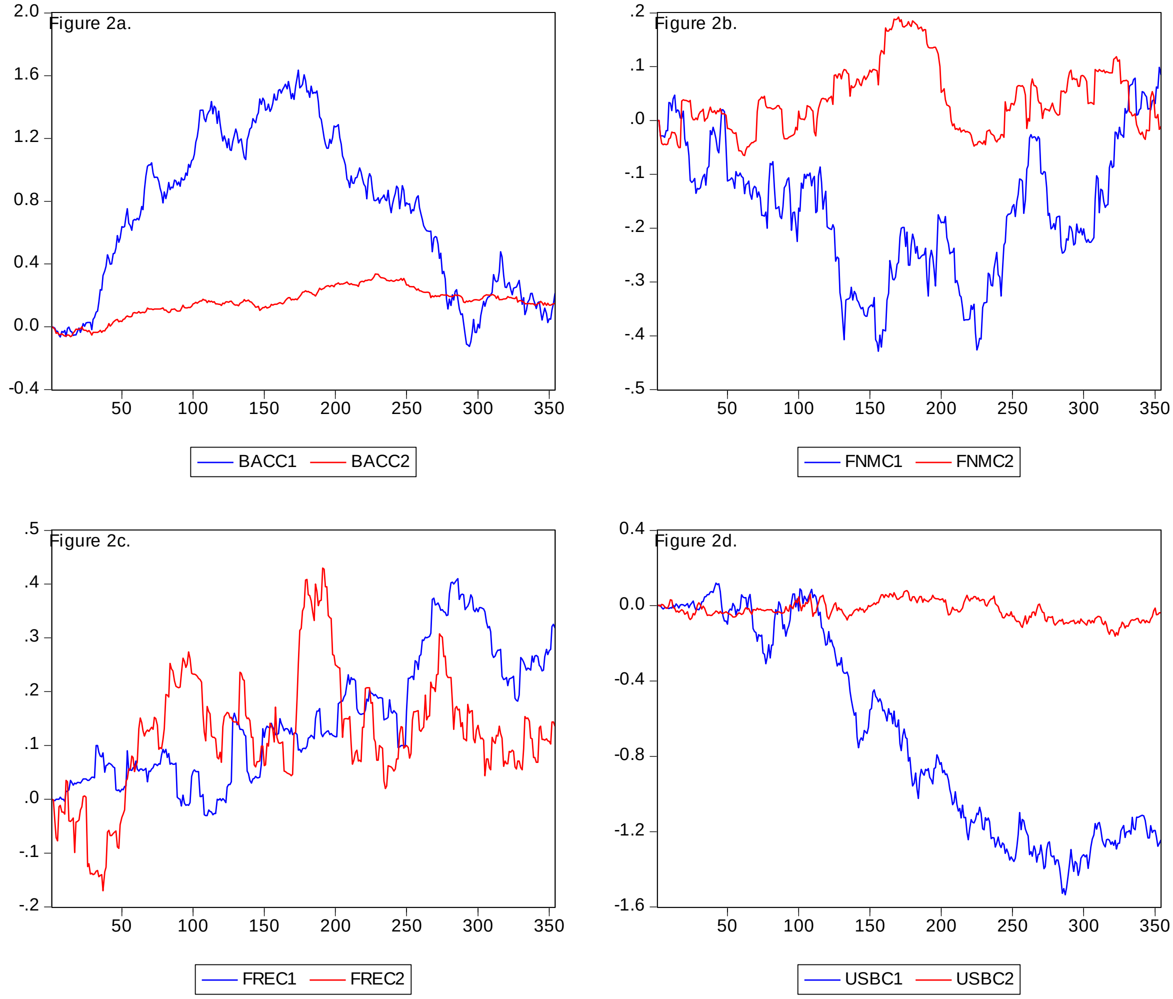
Table A: Summary statistics for prices and %-changes in prices before/after trade ban

Before-After Ban 3/25/2008 – 9/19/2008	*Closing prices Before-After Ban*			*Returns = dln(pt/pt-1) Before-After Ban*		
Firm	*Mean Before After*	*Std. dev. Before After*	*CV(%) Before After*	*Mean Before After*	*Std. dev. Before After*	*CV(%) Before After*
Ambac Fin. Group, Inc.	4.11	1.90	46.0	-0.0044	0.1267	28.8
(ABK)	1.33	0.62	46.6	-0.0089	0.1413	15.9
American Intl. Group, Inc.	31.61	10.76	34.0	-0.0226	0.1186	5.3
(AIG)	1.48	0.62	42.2	-0.0100	0.1170	11.7
Adv. Micro Devices Inc.	6.00	0.90	15.0	-0.0013	0.0370	28.5
(AMD)	2.63	0.66	25.1	-0.0014	0.0687	49.1
Bank of America Corp.	30.63	4.69	15.4	-0.0023	0.0519	22.6
(BAC)	11.99	6.47	54.0	-0.0115	0.1100	9.6
BB&T Corp.	28.41	4.28	15.0	0.0016	0.0439	27.4
(BBT)	22.40	5.85	26.1	-0.0036	0.0600	16.6
Coer d'Alene Mines Corp.	2.69	0.71	26.4	-0.0062	0.0467	7.5
(CDE)	0.76	0.18	23.6	-0.0005	0.1002	200.4
Colonial Banc Group Inc.	6.75	1.66	24.8	-0.0008	0.0714	89.3
(CNB)	1.90	1.62	85.3	-0.0170	0.1678	9.9
Capital One Financial Corp.	43.78	4.93	11.2	0.0002	0.0439	219.5
(COF)	23.02	9.75	42.3	-0.0065	0.0889	13.7
Walt Disney Co.	31.64	1.36	4.2	0.0003	0.0164	54.7
(DIS)	20.87	2.65	12.6	-0.0028	0.0448	16.0
Ford Motor Co.	5.97	1.28	21.4	-0.0010	0.0442	49.1
(F)	2.26	0.48	21.2	0.0002	.0785	392.5
Fannie Mae	17.44	10.24	58.5	-0.0226	0.2351	10.4
(FNM)	0.67	0.17	25.4	-0.0016	0.1192	74.5
Freddy Mac	14.97	9.93	66.0	-0.0218	0.2051	9.4
(FRE)	0.71	0.18	25.3	-0.0018	0.1171	65.1
General Motors Corp.	15.16	4.41	29.1	-0.0045	0.0521	11.6
(GM)	3.72	1.40	37.4	-0.0105	0.1117	10.6
MBIA Inc.	9.14	3.57	38.9	0.0002	0.0952	476.0
(MBI)	5.13	1.71	33.3	-0.0024	0.1051	43.8
Micron Tech. Inc.	6.34	1.47	23.2	-0.0025	0.0396	15.8
(MU)	3.32	0.79	23.8	0.0009	0.0821	91.2
Regions Financial Corp.	13.72	4.77	34.7	-0.0030	0.0641	21.4
(RF)	6.72	2.84	42.3	-0.0081	0.1028	12.7
Sprint Nextel Corp.	8.19	0.94	11.6	0.0003	0.0406	135.3
(S)	2.88	0.77	26.7	0.0004	0.0959	239.8
Synovus Financial Corp.	10.05	1.18	11.7	-0.0000	0.0451	451.0
(SNV)	5.87	2.50	42.4	-0.0067	0.0839	12.5
US Bancorp	30.26	2.29	7.5	0.0007	0.0333	47.6
(USB)	20.72	6.64	32.0	-0.0064	0.0698	10.9
Wells Fargo & Co.	27.48	2.71	9.8	0.0013	0.0437	33.6
(WFC)	22.20	7.27	32.7	-0.0061	0.0886	14.5

Figures 1a-1d: Uptick rule simulations under Normally-distributed ‘news shocks’



Figures 2a-2d: Uptick rule simulations under Cauchy-distributed ‘news shocks’



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