Estimating the Extent of Market Herding in the Philippine Equities Market

Carolina P. Austria, CPA, Ph.D., works as a Bank Officer V at the Department of Economic Research of the Bangko Sentral ng Pilipinas and can be emailed at austriacp@bsp.gov.ph or carolina.austria@gmail.com. The views expressed in this research paper are those of the author and do not necessarily represent those of the BSP or BSP policy.
1. Introduction

For the past few years, the Philippine Stock Exchange Index (PSEi), the index price of the Philippine equities market, has been on a sharp uptrend breaching the 6000, 7000, and 8000 index mark in January 2013, April 2013, and April 2015, respectively, and reaching an all-time high of 8,127.48 on April 10, 2015. The said index increase was the fastest in Asia (Chart 1), resulting in a price-to-earnings (P/E) ratio which is second only to Indonesia (Chart 2). The said price trend raised questions on whether the increases in the PSEi reflected true improvements in the profitability of Philippine businesses or are simply a consequence of market herding. This question is non-trivial. Stock price index increases which are driven by greater profitability and stronger fundamentals are sustainable. On the other hand, an uptrend in prices which is driven by market herding is unsustainable and poses risks of asset price bubbles, with prices abruptly and sharply declining once market herding reverses.¹ Determining the source of price movements — whether these are driven by fundamentals or market herding — is therefore critical so that regulatory authorities can correctly assess market stress conditions and address financial stability issues.

Measuring market herding is, however, no easy task – market herding is time varying, can be volatile, and has to be estimated and derived from other data, often with a low degree of confidence.

Chart 1: Selected Asian Stocks (in index pts, 02 June 2017)

A possible solution to address the above market herding measurement issues was proposed by Hwang and Salmon (2004) who posited that the degree of market herding can be measured using the relative dispersion of the betas for all the assets in the markets. When there is herding towards the market portfolio, the cross-sectional variance of the estimated betas will decrease so that investors herd around the market consensus. This approach, hereafter termed the Hwang and Salmon model, has been used in a number of economies, including South Korea and the United States (Hwang and Salmon, 2004); Ukraine (Zaharheyeva, 2008); France, UK, Italy, and Germany (Khan and Hassairi, 2011); Romania (Pop, 2011); the Euro area (Mobarek & Mollah, 2014); Bangladesh (Ahsan and Sarkar, 2012); Canada (Hachicha, 2010); and Central and Eastern Europe (Angela-Maria, Maria, and Miruna, 2015). Building on this common estimation methodology in the literature, this paper provides a similar market

¹ Asset price reversals and extreme volatility pose important financial stability concerns such that equity index is one of the most commonly used variables in economic literature to assess financial stability, with above trend growth in index or very high levels of market-to-book value considered indicative of an equity price bubble. To cite, Gadanecz and Jayaram (2009) listed six main sectors which are commonly used in the literature to assess financial stability: real sector (GDP growth, fiscal position of the government, and inflation), corporate sector (leverage, expense ratios, net foreign exchange exposure to equity, number of applications for protection against creditors), household sector (net assets, net disposable income), external sector (real exchange rates, foreign exchange reserves, current account, capital flows, maturity/currency mismatches), financial sector (monetary aggregates, real interest rate, risk measures for the banking sector, banks’ capital and liquidity ratios, loan book quality, stand-alone credit ratings, and concentration/systemic focus of banks’ lending activities), and financial markets (equity indices, corporate spreads, liquidity premia, and volatility).
herding estimate for the Philippines. It is structured as follows: Section 2 briefly discusses related literature; Section 3 presents and analyzes the estimates for the Philippines; while Section 4 discusses market herding in light of the Philippine Composite Index of Financial Stress (PCIFS). Section 5 concludes.

2. Related Literature

2.1 Market Herding

Economic and finance models are underpinned by concepts of market efficiency. Many models assume that market prices, particularly in the long term, are anchored on fundamental values and that market agents make rational decisions consistently. However, this is not true. There are many inefficient market behavior including reflexivity or the market’s tendency to self-fulfill its expectations (Soros, 2003); underweighting of outcomes that are merely probable in comparison with outcomes that are obtained with certainty which results in excessive risk aversion or risk seeking or in the attractiveness of both insurance and gambling (Kahneman and Tversky, 1979); and underreaction of stock prices to news such as earning announcements and overreaction to a series of good or bad news (Barberis et al., 1998).

Market agents are also observed to engage in market herding where they follow a trend, imitate the observed decisions of others, or match the movements in the market rather than follow their own beliefs and information (Hwang and Salmon, 2004). Andreassen and Kraus, for example, noted in an experiment that subjects tracked prices: they sell when prices rise and buy when prices fall even when the prices offered were a random walk Barberis et al. (1998) had similar results. They found that a forecast change in stock price level is higher after a series of past price increases than a series of price decreases, indicating that investors chase trends once they believe that these exist.

There are various explanations for market herding. To cite, Shleifer and Vishny (1997) noted that textbook discussions of market efficiency assume that arbitrage in financial markets requires no capital and entails no risk. This is not true in reality as all arbitrages require capital and are risky. Moreover, professional arbitrage is conducted by a relatively small number of highly specialized investors who rely on other people’s money and are therefore required to report the short- and medium-term results of their operations. Such short investing horizon and risk aversion sometimes motivate investors to simply follow the market.

Long et al. (1990), on the other hand, argued that market dynamics limit the opportunities for arbitrage. Short-horizon arbitrageurs take the opposite trading position of market herders or trend chasers believing that a given trend is untenable and would soon reverse. However, it is possible that market herders or trend chasers might take even more extreme positions and further reinforce the ongoing price movement trend. If the arbitrageur is forced to liquidate his position before the prices move toward the true fundamental values, he suffers a loss. This uncertainty creates a fear of loss which limits an arbitrageur’s activities and induces him or her to simply imitate the market. Information asymmetry could also explain market herding. Market agents sometimes think that other
market participants are better informed than they are, driving them to set aside their own information in favor of perceived market trends (Hwang and Salmon, 2004). Market herding is observed to vary in different conditions. Using holdings of individual funds in emerging market mutual funds over the period 1996:1 to 1999:3, Borensztein and Gelos (2000) found that degree of herding among funds is significant but not dramatic; herding is much more widespread among open-ended than among closed-end funds but is not more prevalent during crisis than during tranquil times. In emerging markets, funds tend to follow momentum strategies, selling past losers and buying past winners, but they are not panic-driven irrational institutions. Shyu and Sun (2010) had similar findings with Taiwan as their case country for emerging markets. They found evidence of market herding in Taiwan’s stock market. This herding is not driven primarily by impulse or instinct but is instead driven by information cascades. Herding behavior is also observed among Dutch pension funds in sovereign bond investments (Koetsier and Bikker, 2017). Using data from 67 large Dutch pension funds that invest in 109 countries, the authors found evidence of market herding with institutional factors, the macroeconomic environment, and the financial market environment as some of the determinants of herding behavior. Interestingly, however, Koetsier and Bikker (2017) found that the level of market development did not change the results; the Dutch pension funds had the same herding behavior whether in emerging or in developed economies. Results are somewhat similar for Demirer, Kutan, and Zhang (2012) who found evidence of herding behavior for American Depositary Receipts (ADR) in only one out of 19 countries examined. Indeed, literature points to non-uniform herding behavior in different economies, requiring herding estimates to be specific for each market.

2.2 Methods for Estimating Market Herding

Various methods may be used to estimate market herding. Mensah and Yang (2008), for example, estimated market herding via the dispersion of analysts’ earnings forecasts. Christie and Huang (1995), on the other hand, analyzed the cross-sectional standard deviation of individual stock returns and then ran a regression on a constant and two dummy variables designed to capture extremely positive and negative market returns. They argued that during periods of market stress rational asset pricing would imply positive coefficients on those dummy variables while herding behavior would result in negative coefficients. This approach is reasonable but has been criticized because market stress does not necessarily imply that the market as a whole should show either large negative or positive returns. It is possible that herding could pertain to a considerable reallocation towards a particular sector. This, of course, would not show as a dramatic change in the aggregate data. Thus, defining herding as only arising when there are large positive or negative returns for the aggregate market could exclude certain types of herding behavior. Another approach to measuring market herding was proposed by Hwang and Salmon (2004) who argued that the degree of market herding can be measured using the relative dispersion of the betas for all the assets in the markets. When there is herding towards the market portfolio, the cross-sectional variance of the estimated betas will decrease so that investors herd around the market consensus. Their logic is as follows. In the Capital Asset Pricing Model (CAPM), the following equilibrium holds:

\[ E(t)(r_{it}) = \beta_{int}E(t)(r_{mt}) \]

where \( E(t) \) is the term for expectations, \( r_{it} \) is the return on asset \( i \) at time \( t \), \( \beta_{int} \) is the systematic risk measure, and \( r_{mt} \) is the return on market at time \( t \).
The conventional CAPM assumes that $\beta_{\text{m}}$ does not change over time. However, Hwang and Salmon (2004) argued that there is considerable evidence that the betas do in fact vary over time. Such variation in the betas could happen when a firm changes its capital structure substantially or if a company changes its main business area, say, from manufacturing to the service sector. However, since changes in business structure and focus happen slowly, Hwang and Salmon (2004) posited that a significant portion of the time variation in $\beta_{\text{m}}$ reflects changes in investor herding rather than fundamental changes in $\beta_{\text{m}}$ or the equilibrium relationship between $E_r(r_{\text{m}})$ and $E_r(r_{\text{f}})$. When herding occurs, the betas become biased as investors’ beliefs shift to follow market sentiments. That is, investors disregard the equilibrium (or true CAPM) value for $\beta_{\text{m}}$ and move towards matching the returns on the individual assets with that of the market. For example, when the market increases significantly, investors will try to buy overvalued assets (relative to the market) and sell undervalued assets. Such trading strategies result in a lower standard deviation in the betas for the individual assets for that particular time period. Hwang and Salmon (2004) noted that the results of their research resonate with Christie and Huang (1995) who concluded that during market crises, herding begins to disappear. However, when the market is quiet and investors are confident of the direction in which markets are heading, market herding increases.

The above concepts on market herding estimation were operationalized by Hwang and Salmon (2004) as follows:

1. Run the standard CAPM model per month using daily data to determine the betas of each of the stocks which comprise the index. For example, if there are 500 stocks, then there will be 500 regression equations for each month, with each month containing 20 or 21 data points. The regression equation is as follows:

$$r_{\text{id}} = \alpha_{\text{id}} + \beta_{\text{id}}r_{\text{m}} + \epsilon_{\text{id}}$$

where $r_{\text{id}}$ is the daily return on asset $i$, $\alpha_{\text{id}}$ is the constant coefficient or the manager’s alpha asset $i$ at time $t$, $\beta_{\text{id}}$ is the systematic risk measure, $r_{\text{m}}$ is the return on market at time $t$, and $\epsilon_{\text{id}}$ is the error term.

2. Compute for the log of the standard deviation of the betas obtained for each month using the formula below. Note that the dispersion of the betas is a crucial variable in determining market herding. When the market is herding, the standard deviation is low. When the market is not herding, the standard deviation is high.

$$\text{Std}_{\text{c}}\beta_{\text{m}} = \sqrt{\frac{\sum_{i=1}^{N_i} (\bar{\beta}_{\text{id}} - \bar{\beta}_{\text{m}})}{N_t}}$$

where $\text{Std}_{\text{c}}\beta_{\text{m}}$ is standard deviation of the betas of the stocks, $\bar{\beta}_{\text{id}}$ is the beta for each stock per month, $\bar{\beta}_{\text{m}}$ is the average beta for all stock per month, and $N_t$ is the sample size.

3. To control for market return and market volatility, a state-space model which will provide the proxy for the herding measure can be used, as follows:

$$\ln[\text{Std}_{\text{c}}(\beta_{\text{m}})] = \mu_m + H_{\text{mt}} + \epsilon_{\text{mt}}$$

where $\ln[\text{Std}_{\text{c}}(\beta_{\text{m}})]$ is the log of the standard deviation of the betas of the stocks for each month, $\mu_m$ is the constant, $H_{\text{mt}}$ the state variable for market herding, $\ln\sigma_{\text{mt}}$ is the market volatility variable, $c_{\text{m}}r_{\text{mt}}$ is the market return variable, $v_{\text{mt}}$ is the error term for the signal equation, and $\eta_{\text{mt}}$ is the error term for the state equation.
4. To arrive at the quantifiable herding measure, $H_{mt}$ is transformed using the formula below. Note that the greater the value of $H_{mt}$ is, the greater is the market’s tendency to herd. Note that the degree of herding is measured as the log of the standard deviation of the betas obtained for each month.

$$H_{mt} = \ln(1 - h_{kt})$$

where $H_{mt}$ is the resulting measure of market herding.

3. Estimating the Extent of Market Herding in the Philippine Equities Market

For the Philippine estimate, I included data for the stock market index and 30 Philippine equities for the period January 1, 1990 to October 16, 2017. Using the above state space model on these data resulted in the following market herding estimate:

The results show that for the period above, Philippine market herding estimates ranged from 0.71 in January 1990 to 0.88 in May 2017 with the lowest point registered on April 6, 2001 at 0.19 and the peak observed on August 18, 2014 at 0.88. Substantial declines in market herding were observed on 04/01/1997, 05/01/2000, 06/01/2004, 04/01/2006, 12/1/2008, and 06/01/2011. It can be noted that these dates correspond to or were close to critical periods of market stress, including the Asian crisis in 1997; the US dotcom bubble in 2000, the Philippine presidential election in 2004 in which President Gloria Arroyo won after a tumultuous period when President Estrada was overthrown; the declaration of a state of emergency in the Philippines due to persistent coup rumors in 2006; the global financial crisis in 2008; and the sharp drop in the stock markets in Europe, the US, and Asia due to fears of a European sovereign debt crisis in 2011.

Another interesting observation of the graph is the fact that, currently, market herding levels are at an all-time high since July 1, 2013, with measures consistently higher than the levels during the 1997 Asian Financial Crisis and the 2008 Global Financial Crisis. Such levels are instructive. It could imply that the current up trend in the equities market is not driven solely by strong corporate and macroeconomic fundamentals but also by market herding behavior and there is therefore the risk of a sharp drop similar to the 1997 and 2008 crises.
4. Market Herding and the PCIFS

The Bangko Sentral ng Pilipinas (BSP) produces a financial stress index called the Philippine Composite Index of Financial Stress (PCIFS) to gauge the overall stress in the Philippine financial markets as well as in the country’s four smaller or sub-markets: money, bond, equities, and foreign exchange markets (Table 1). Indicators included in the PCIFS were chosen based on three criteria. First, the indicators should include level shifts in important variables, volatilities in certain prices, and measures of risk premia such as interest differentials and debt spreads. Second, the indicators should be available on a daily basis to capture the dynamic changes inherent in the financial markets. Third, the indicators should be able to capture features of financial stress such as flight to liquidity and flight to safety. To do this, the indicators should have created some signals during past episodes of financial stress.

Table 1

<table>
<thead>
<tr>
<th>Money market</th>
<th>Bond market</th>
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<tr>
<td>• Secondary market yield of a 91-day Treasury bill (T-bill)</td>
<td>• Secondary market yield of a 10-year Treasury bond (T-bond)</td>
</tr>
<tr>
<td>• Spread between banks’ prime lending rate and RRP rate</td>
<td>• JP Morgan emerging markets bond index plus Philippine sovereign spread (EMBI + Philippines)</td>
</tr>
<tr>
<td>• Interbank call loan (ICBL) rate</td>
<td>• 5-year sovereign credit default swap (CDS) spread</td>
</tr>
<tr>
<td>• 5-year sovereign credit default swap (CDS) spread</td>
<td>• JP Morgan corporate emerging market bond broad index (CEMBI) Philippine yield</td>
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<tr>
<th>Equities market</th>
<th>Foreign exchange market</th>
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<tbody>
<tr>
<td>• Inverse of Sharpe ratio</td>
<td>• JP Morgan USD/PHP currency option volatility index</td>
</tr>
<tr>
<td>• 30-day PSEi volatility</td>
<td>• Inverse of peso dollar exchange rate 2-year CMAX</td>
</tr>
<tr>
<td>• Inverse of PSEi 2-year CMAX</td>
<td>• Peso dollar exchange rate GARCH (1,1) 1-month volatility</td>
</tr>
</tbody>
</table>

Source: BSP

Note that the higher the PCIFS is, the greater is the financial stress. And to determine if an event is stressful enough to warrant an immediate policy response or closer monitoring, the BSP has established upper (immediate policy response) and lower thresholds (closer monitoring). The upper distress threshold, currently set at 0.75, is used to measure extreme stress levels or stress periods that could potentially lead to a financial crisis. An example of such a period is the global financial crisis in 2008-2009 when almost all PCIFS variables were at very high levels. It should be noted that this threshold is dynamic in nature since the value is not permanently set at 0.75. Instead, it depends on the value of the benchmark period. The lower distress threshold is based on the results of noise-to-signal tests and is set as three consecutive weeks when the PCIFS index is at least one standard deviation above the previous quarter’s average PCIFS. The distress threshold must be breached in at least three distinct markets before a warning is raised. With the above definitions, an example of a stress episode which breached the lower distress threshold is the “taper tantrum” in 2013. Greater details on the overall PCIFS and the Equity Sub-Market Stress Index for the period January 2005 to May 2017 is shown in Charts 4 and 5 below.
Chart 4 shows that the overall stress index reached its peak in 2009 and that, currently, stress levels are relatively low compared to previous years. Chart 5, on the other hand, shows that the equities market is showing some signs of distress, breaching the threshold in the earlier part of 2016. It can be argued that while these charts are useful, analytical tools which could provide additional information are still necessary to come up with a cogent analysis of the financial markets. This is where the market herding measure could prove invaluable. By providing data on market behavior, the market herding measure provides a more nuanced analysis of the stress index. An example of such supplementary analysis is shown in Charts 6 and 7, where the market herding measurement is placed vis-a-vis the PCIFS and the equity sub-market stress index.

Juxtaposing the PCIFS and the equity sub-market index with the market herding measurement result in some interesting findings:

1. Market herding is observed to resonate well with the PCIFS, with the data aligned with economic theory: market herding is high (low) when market stress is low (high). After the Global Financial Crisis, for example, market herding was on a sharp downtrend as the market experienced severe stress; while currently, market herding is high given the low overall market stress conditions. The co-movement between market herding and equity sub-market index is, however, more tenuous. The equity submarket index appears too volatile when compared with market herding. The above finding is easy to explain. It appears that market herding behavior is affected by many factors and performance in multiple markets. Evidently, market agents consider the overall market...
situation in their decisions. They don’t look only at the equity markets; they also look at interest rates, inflation, exchange rates, etc.

2. Market herding provides a supplementary tool to analyze the market stress index. Consider for example the Global Financial Crisis. In 2008, market herding declined as overall market stress went up, consistent with economic theory; that is, investors foresaw a market correction to reflect the projected adjustments in corporate fundamentals (e.g., profitability, solvency, liquidity, etc.). More recently, however, we note that the PSEi declined and the equity submarket stress index increased, and yet market herding remains consistently high, indicating that the market believes that the current market stress does not reflect fundamentals and there is no forthcoming market correction. Thus, the PSEi declined not because there was a fundamentals-based market stress but because the market was herding: it reacted adversely to external events, including the sudden capital flows to the US in anticipation of favorable US election results, and the Philippine government’s foreign policy shift in 2016.

3. To date, market herding remains high and therefore bears watching.

5. Concluding Remarks

The Hwang and Salmon model shows that the market herding in Philippine equity markets is on an uptrend since 2012, with estimates for 2015-2017 highest since 1990 and even higher than the levels in 2008. Market herding estimates indicate that the equity market bears watching as the recent stock price uptrend is not only driven by improving corporate and macroeconomic fundamentals but also by a consistently high market herding measure.

Juxtaposing the market herding measure against the overall PCIFS and the equity submarket index provide intuitive results. First, market herding compares well with overall PCIFS. Consistent with theory, market herding is high when market stress is low and vice-versa. Second, market herding provides a good supplementary tool to analyze the equity submarket index. The market herding measure, for example, shows that the recent sudden decline in the PSEi was due to the market’s reaction to external factors such as the capital outflows from the Philippines to the US in light of favorable forecasts for the US elections and adverse reaction to President Duterte’s foreign policy shift. Through the market herding measure, it can be concluded that the market is not foreseeing a correction in the fundamentals such as the forecast profitability of Philippine firms.

The market herding measure using the Hwang and Salmon model could prove useful for analyzing the conditions in Philippine equity markets. In the future, this measure as well as specific fundamental variables (profitability, liquidity, solvency, etc.) could be used to further analyze the PCIFS and the equity submarket index.

Annex 1

List of Philippine Equities Included in the Study

<table>
<thead>
<tr>
<th>AC PM Equity</th>
<th>BLOOM PM Equity</th>
<th>GLO PM Equity</th>
<th>MBT PM Equity</th>
<th>SCC PM Equity</th>
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<tbody>
<tr>
<td>AEV PM Equity</td>
<td>BPI PM Equity</td>
<td>GTCAP PM Equity</td>
<td>MEG PM Equity</td>
<td>SM PM Equity</td>
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<td>AGI PM Equity</td>
<td>DMC PM Equity</td>
<td>ICT PM Equity</td>
<td>MER PM Equity</td>
<td>SMC PM Equity</td>
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<tr>
<td>ALI PM Equity</td>
<td>EDC PM Equity</td>
<td>JFC PM Equity</td>
<td>MPI PM Equity</td>
<td>SMH PM Equity</td>
</tr>
<tr>
<td>AP PM Equity</td>
<td>EMP PM Equity</td>
<td>JGS PM Equity</td>
<td>PCOR PM Equity</td>
<td>TEL PM Equity</td>
</tr>
<tr>
<td>BDO PM Equity</td>
<td>FGEN PM Equity</td>
<td>LTG PM Equity</td>
<td>RLC PM Equity</td>
<td>URC PM Equity</td>
</tr>
</tbody>
</table>

A fundamentals-based market stress would have resulted in a drop in market herding which is not seen in the data.
References


