COVID-19 Pandemic and Investor Herding in International Stock Markets
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Abstract
This study examines the effect of the recent novel coronavirus pandemic on investor herding behavior in global stock markets. Utilizing a daily newspaper based index of uncertainty associated with infectious diseases, we show a strong association between herd formation in stock markets and COVID-19 induced market uncertainty. The herding effect of COVID-19 induced market uncertainty is particularly strong for emerging stock markets as well as European PIIGS stock markets that include some of the hardest hit economies in Europe by the pandemic. The findings establish a direct link between the recent pandemic and investor behavior in financial markets.

Keywords: COVID-19; International Stock Markets; Investor Herding.

JEL Codes: C22, G15.

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1. Introduction

Herding behavior has been shown to exacerbate price fluctuations and drive pricing inefficiencies in financial markets (e.g. Bikhchandani and Sharma, 2001; Blasco et al, 2012; Demirer et al., 2019). Irrespective of the nature of such behavior among investors, rational or otherwise, the literature generally suggests that herding is more prevalent during periods of market stress or heightened uncertainty. Although a large number of studies have examined the presence of herding behavior in financial markets from different angles and using a wide range of samples (e.g. see Uwilingiye et al., 2019 for a recent review), the literature has not yet examined the role of the recent COVID-19 pandemic in this context as a driver of herding behavior among market participants. Given that the recent COVID-19 pandemic has triggered a massive spike in uncertainty, quickly transitioning from a healthcare crisis into an economic one, this paper examines the role of the pandemic as a driver of investor herding in international stock markets by utilizing a daily newspaper based index of financial uncertainty associated with infectious diseases, recently developed by Baker et al. (2020).

The earlier literature has already established the role of time-varying disaster risks as a factor that can explain the high excess returns and volatility observed in stock markets via its effects on investment growth or consumption patterns (e.g. Barro and Ursúa,, 212; Gourio, 2012; Wachter, 2013, among others). Clearly, the probability and size of disasters lead to a great deal of uncertainty, which in turn can contribute to cash flow as well as discount rate shocks in stock valuations. However, quantifying the uncertainty related to such risks has been a challenge in most studies as it is often hard to distinguish between disaster induced uncertainty from the component of uncertainty that is driven by non-disaster related factors. To that end, the recently developed newspaper-based index of Baker et al., (2020), which tracks equity market volatility (EMV), in
particular the movements in the Chicago Board Options Exchange (CBOE)'s Volatility Index (VIX), due to infectious diseases, provides an interesting opening. This index, presented in Figure 1, highlights the massive increase in uncertainty due to the pandemic over the recent months. The availability of this index at a daily frequency further allows us to examine the possible link between time-varying herding in stock markets and pandemic induced market uncertainty from a novel perspective. To the best of our knowledge, ours is the first study to examine herding behaviour in international stock market in this context. Our analysis is related to a growing literature dealing with the effect of COVID-19 on financial markets (Akhtaruzzaman et al., 2020; Ashraf, 2020; Conlon, 2020; Conlon et al., 2020; Goodell, 2020; Sharif et al., 2020).

[INSERT FIGURE 1]

Our findings indicate a strong association between herd formation in stock markets and COVID-19 induced financial market uncertainty. The herding effect of COVID-19 driven uncertainty is particularly strong for emerging stock markets as well as European PIIGS stock markets that include some of the hardest hit economies in Europe by the pandemic. The above findings establish a direct link between the recent pandemic and investor behavior in financial markets, which has not been previously revealed.

The remainder of the paper is organized as follows. Section 2 presents the data and testing methodology. Section 3 provides the discussion of the empirical findings and Section 4 concludes.

2. Data and testing methodology

2.1. Data

We utilize daily data for Morgan Stanley Capital International (MSCI) indexes in US Dollars for 49 individual countries and the overall MSCI World index over the period of 1st
January, 2019 to 10\textsuperscript{th} August 2020. The source of our data is DataStream of Thomson Reuters. Besides examining all countries together as a group, we examine herd formation across various country groups based on the suggestion by Bikhchandani and Sharma (2001) that herd formation would be more likely to occur at the level of investments with similar characteristics where investors face similar decision problems.\textsuperscript{1} For this purpose, we sort the countries into advanced and emerging country groups based on the MSCI country classification.\textsuperscript{1} We further explore herding within a group of major commodity exporters (Canada, Norway, Australia, New Zealand and Chile), BRICS nations (Brazil, Russia, India, China and South Africa) and PIIGS (Portugal, Ireland, Italy, Greece and Spain) in order to account for the similarity in economic fundamentals as well as the investment allocations maintained by global investment funds.

Since the focus of our analysis is to check for the presence of herding over the ongoing COVID-19 period, we split the data into equal number of observations (i.e., 159 data points) from 23\textsuperscript{rd} May, 2019 to 31\textsuperscript{st} December, 2019 and 1\textsuperscript{st} January, 2020 to 10\textsuperscript{th} August, 2020 to account for possible structural breaks in herding patterns before and during the outbreak of the Coronavirus. Further, to study the possibility of time-varying herding, we conduct a time-varying estimation of our model (which we discuss below), with the period of 1\textsuperscript{st} January, 2019 to 22\textsuperscript{nd} May, 2019 used as the size of the rolling window, i.e., 102 observation. Understandably, this ensures that we are able to analyze the evolution of the herding coefficient estimates over equal periods before and during the ongoing pandemic.

\textsuperscript{1} Stock market classifications by MSCI are available at \url{https://www.msci.com/market-classification}.
2.2. Testing methodology

Some of the pioneering works in the strand of the literature that deals with herding tests in financial markets include Christie and Huang (1995) and Chang et al. (2000) who propose a return dispersion based methodology to detect herding. These herding tests focus on the cross-sectional behavior of asset returns within portfolios that include assets of similar characteristics. Following Chang et al., (2000), we use the cross-sectional absolute standard deviations (CSAD) across country returns (and the various categorizations) and examine the non-linear relation between the level of return dispersion and the aggregate market return, as captured by the MSCI World index.

The CSAD statistic, used as a measure of return dispersion, is formulated as follows:

\[
CSAD_t = \frac{1}{N} \sum_{i=1}^{N} |R_{i,t} - R_{m,t}|
\]  

(1)

where \(R_{i,t}\) and \(R_{m,t}\) is the log-returns on stock index of a specific country \(i\) and the overall index for period \(t\), respectively; \(N\) is the number of stock indexes in the portfolio at time \(t\).

Chang et al., (2000) suggest that during periods of market stress, one would expect return dispersion (\(CSAD_t\)) and the aggregate market return (\(R_{m,t}\)) to have a nonlinear relationship such that herding, if present, would yield lower dispersion across country returns during large aggregate market fluctuations. Following the argument by Christie and Huang (1995) that the probability of herd formation is greater during periods of market stress and large price movements, the

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2 Demirer et al. (2010) provide a review of the different testing methodologies based on return dispersion.

3 We also repeat our analysis by computing the cross-sectional standard deviation \((CSSD_t) = \sqrt{\frac{\sum_{i=1}^{N} (R_{i,t} - R_{m,t})^2}{N-1}}\) statistic instead of CSAD. We obtained qualitatively, as well as quantitatively similar results, which are available upon request from the authors.

4 Since data is available for all the countries before 1st January of 2019, note we do not lose any observation while computing log-returns used in our model.
benchmark model is formulated based on the following quadratic model of return dispersion and
market return:

\[ CSAD_t = \alpha_0 + \alpha_1 |R_{m,t}| + \alpha_2 R_{m,t}^2 + \varepsilon_t \]  \hspace{1cm} (2)

The presence of herding then is tested via the following hypotheses:

- \( H_0 \): In the absence of herding effects, we expect in Eq. (2) that \( \alpha_1 > 0 \) and \( \alpha_2 = 0 \)
- \( H_{1a} \): If herding behavior exists, we expect \( \alpha_2 < 0 \).
- \( H_{1b} \): If anti-herding behavior exists, we expect \( \alpha_2 > 0 \).

As noted earlier, given the dynamic nature of possible herding formation, we utilize a time-varying
approach via rolling regressions of the model in Eq. (2).

3. Empirical Findings

The results from the static model in Eq. (2) are reported in Table 1 for the full-sample, i.e.,
23rd May, 2019 to 10th August, 2020, and pre- and during COVID-19 periods. As indicated by the
non-negative estimates for the herding coefficient \( \alpha_2 \), the static dispersion model yields no
evidence of herding across any of the country groups. If anything, when significance holds
particularly for the full sample, the results indicate the presence of anti-herding behavior across all
the markets and the various categorizations, implied by the positive and significant \( \alpha_2 \) estimates.

[INSERT TABLE 1]

Balcilar et al. (2013) argue that the static model in Eq. (2) leads to misleading conclusions
regarding the presence of herd behavior as parameters in this specification are assumed to be
constant over time. Given this and considering that investor behavior can be characterized to be
dynamic and time-varying, depending on the market conditions, we resort to a rolling-window
approach following Stavroyiannis and Babalos (2017). Figure 2 reports the evolution of the \( t-\)
statistics for the herding coefficient in Eq. (2) across the various country groups over the full sample period of 23rd May, 2019 to 10th August, 2020. Understandably for herding, we are looking to identify periods for which the \( t \)-statistics are significantly negative, i.e., less than or equal to -1.645 and -1.96 corresponding to the 10% and 5% levels of significance.

[INSERT FIGURE 2]

As seen in Figure 2, we are able to detect some evidence of herding primarily during the period that primarily corresponds to the COVID-19 outbreak. More specifically, periods during which herding is detected are found as follows: All Countries: 17th March, 2020-7th May, 2020; Advanced: 24th March, 2020-13th May, 2020; Emerging: 16th June, 2020-10th August, 2020 (besides some intermittent episodes in 2019 and early 2020); BRICS: 28th May, 2019-18th July, 2019, and 12th March, 2020-6th May, 2020; PIIGS: 9th March, 2020-8th June, 2020, and; Commodity Exporters: 3rd April, 2020-13th April, 2020 (only at the 10% level of significance). The above evidence suggests that herding in the stock markets is a short-lived phenomenon induced by the instantaneous behavior of investors.

Having detected episodes of herding formation across various international stock market classifications, a crucial question to ask is whether or not we can formally associate significant herding behavior over these periods with the outbreak of the Coronavirus. For this purpose, we resort to a Probit model. We first define two dummy variables: \( D_1 \) and \( D_2 \), which take the value of unity during periods of statistically significant herding at 10% and 5% levels of significance respectively, i.e., for days in Figure 2 when the rolling \( t \)-statistic on \( \alpha_2 \leq -1.645 \) and \( \alpha_2 \leq -1.96 \) and zero otherwise. Then, we use a Probit model to relate this dummy with the infectious disease equity market volatility (EMV) tracker, which has been recently constructed by Baker et al., (2020) as a
newspaper-based index available at the daily frequency from January 1985. This index is based on textual analysis of four sets of terms namely, E: economic, economy, financial; M: “stock market”, equity, equities, “Standard and Poors”; V: volatility, volatile, uncertain, uncertainty, risk, risky; ID: epidemic, pandemic, virus, flu, disease, coronavirus, mers, sars, ebola, H5N1, H1N1, and then obtain daily counts of newspaper articles that contain at least one term in each of E, M, V, and ID across approximately 3,000 US newspapers. The raw EMVID count is scaled by the count of all articles in the same day, and finally, Baker et al., (2020) multiplicatively rescale the resulting series to match the level of the VIX, by using the overall EMV index, and then scaling the EMVID index to reflect the ratio of the EMVID articles to total EMV articles. The EMVID index, presented in Figure 1 over the rolling-window estimation period of 23rd May, 2019 to 10th August, 2020 clearly highlights the spikes (peaking in March of 2020) associated with the impact of the COVID-19 outbreak on financial market uncertainty.

The Probit model to relate the occurrence of herding formation to the pandemic induced uncertainty index is formulated as follows: \( Pr(D_i=1|X) = \Phi(\beta_0 + \beta_1 EMVID) \) where, \( i=1, 2 \); \( Pr \) denotes probability, and \( \Phi \) is the Cumulative Distribution Function (CDF) of the standard normal distribution, with the parameters \( \beta_0 \) and \( \beta_1 \) estimated by maximum likelihood. As can be clearly seen in Table 2, we observe that the EMVID index has a positive and significant effect, suggesting that the pandemic induced financial market uncertainty increases the probability of herding, in a statistically significant manner at least at the 5% level, irrespective of whether we use \( D_1 \) or \( D_2 \) to capture periods of significant herd formation. In other words, EMVID tends to drive herding in the equity markets across countries, as well as in our sub-groups. Interestingly, the strongest pandemic effect on herding formation is observed for emerging stock markets as well as the PIIGS

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5 The index is available at: [http://policyuncertainty.com/infectious_EMV.html](http://policyuncertainty.com/infectious_EMV.html).
countries that include some of the hardest hit European countries by COVID-19 like Italy and Spain. The findings, thus, establish a clear association between pandemic induced financial market uncertainty and herd formation in international stock markets. Evidence on such association extends our limited understanding on the effect of COVID-19 pandemic on investor behavior in international stock markets, which is somewhat comparable to previous findings (e.g., Gleason et al., 2004) that point to a relationship between herding and highly volatile markets. In our case, the EMVID index reflects investor sentiment and the high level of this newspaper based index of uncertainty associated with infectious diseases captures the fear of investors. Under such disaster risks, investors seek for confirmation, leading to significant herding.

4. Conclusion

This study examines the effect of the recent novel coronavirus pandemic on investor herding behavior in global stock markets by utilizing the recently developed newspaper-based index of Baker et al., (2020), which tracks equity market volatility (EMV), in particular the movements in the Chicago Board Options Exchange (CBOE)'s Volatility Index (VIX), due to infectious diseases. Utilizing a combination of rolling window regressions and Probit analysis, applied to daily return data for 49 international stock markets, we document strong association between herd formation in global stock markets and COVID-19 induced financial market uncertainty. The herding effect of COVID-19 driven uncertainty is particularly strong for emerging stock markets and the European PIIGS stock markets that include some of the hardest hit economies in Europe by the pandemic. This finding suggests that herding depends on the development status of the economy under study. Notably, our findings establish a direct link between the recent novel coronavirus
pandemic and investor behavior in financial markets, highlighting the role of disaster risks such as COVID-19 as a potential driver of behavioral patterns in financial markets.

The implications of the above findings matter to both regulators and investors as they confront them with challenges. In fact, the existence of herding behavior might jeopardize market efficiency and limits the possibility of diversification. However, evidence on the behavioral pattern of stock investors in relation to infectious diseases uncertainty can be useful in studying price discovery in stock markets and might help market participants in forming hedging strategies to mitigate downside risk in the stock markets.

For future research, it would be interesting to examine whether or not these behavioral patterns contribute to volatility jumps as well as jump induced risk premia in asset prices.
References


Table 1: Estimates of the Static Herding Model.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Parameters</th>
<th>All Countries</th>
<th>Advanced</th>
<th>Emerging</th>
<th>BRICS</th>
<th>PIIGS</th>
<th>Commodity Exporters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\alpha_0$</td>
<td>0.008***</td>
<td>0.005***</td>
<td>0.01***</td>
<td>0.009***</td>
<td>0.006***</td>
<td>0.006***</td>
</tr>
<tr>
<td>Full-Sample</td>
<td>$\alpha_1$</td>
<td>0.288***</td>
<td>0.258***</td>
<td>0.269***</td>
<td>0.248***</td>
<td>0.146***</td>
<td>0.176***</td>
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<tr>
<td></td>
<td>$\alpha_2$</td>
<td>0.994***</td>
<td>0.301*</td>
<td>1.474***</td>
<td>1.388***</td>
<td>0.915***</td>
<td>1.964***</td>
</tr>
<tr>
<td>Pre-COVID</td>
<td>$\alpha_0$</td>
<td>0.006***</td>
<td>0.004***</td>
<td>0.007***</td>
<td>0.006***</td>
<td>0.005***</td>
<td>0.005***</td>
</tr>
<tr>
<td></td>
<td>$\alpha_1$</td>
<td>0.231***</td>
<td>0.172***</td>
<td>0.22</td>
<td>-0.012</td>
<td>0.004</td>
<td>0.131</td>
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<tr>
<td></td>
<td>$\alpha_2$</td>
<td>1.527</td>
<td>-0.539</td>
<td>3.715</td>
<td>12.887*</td>
<td>8.59</td>
<td>1.774</td>
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<tr>
<td>During-COVID</td>
<td>$\alpha_0$</td>
<td>0.007***</td>
<td>0.006***</td>
<td>0.008***</td>
<td>0.008***</td>
<td>0.005***</td>
<td>0.007***</td>
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<tr>
<td></td>
<td>$\alpha_1$</td>
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<td>0.255***</td>
<td>0.442</td>
<td>0.339</td>
<td>0.313</td>
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<td></td>
<td>$\alpha_2$</td>
<td>-0.36</td>
<td>-0.334</td>
<td>-0.881</td>
<td>-0.473*</td>
<td>-1.306</td>
<td>-0.205</td>
</tr>
</tbody>
</table>

Note: Full-Sample: 23rd May, 2019 to 10th August, 2020; Pre-COVID: 23rd May, 2019 to 31st December, 2020; During-COVID: 1st January, 2020 to 10th August, 2020; The parameters of the model estimated is: $CSAD_t = \alpha_0 + \alpha_1 |R_{m,t}| + \alpha_2 R^2_{m,t} + \epsilon_t$; ***, **, * significant at 1%, 5% and 10% levels, respectively.
Table 2: Estimates of the Probit Model.

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Parameters</th>
<th>All Countries</th>
<th>Advanced</th>
<th>Emerging</th>
<th>BRICS</th>
<th>PIIGS</th>
<th>Commodity Exporters</th>
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<tbody>
<tr>
<td></td>
<td>$\beta_0$</td>
<td>-2.456***</td>
<td>-2.093***</td>
<td>-2.204***</td>
<td>-1.026***</td>
<td>-2.464***</td>
<td>-2.632***</td>
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<tr>
<td></td>
<td>$\beta_1$</td>
<td>0.064***</td>
<td>0.050***</td>
<td>0.070***</td>
<td>0.027***</td>
<td>0.092***</td>
<td>0.022***</td>
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<tr>
<td>$D_1$</td>
<td>$\beta_0$</td>
<td>-2.551***</td>
<td>-2.166***</td>
<td>-2.599***</td>
<td>-1.420***</td>
<td>-2.460***</td>
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<tr>
<td></td>
<td>$\beta_1$</td>
<td>0.056***</td>
<td>0.042***</td>
<td>0.075**</td>
<td>0.034***</td>
<td>0.077***</td>
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<tr>
<td>$D_2$</td>
<td>$\beta_0$</td>
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<td>-2.093***</td>
<td>-2.204***</td>
<td>-1.026***</td>
<td>-2.464***</td>
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<tr>
<td></td>
<td>$\beta_1$</td>
<td>0.064***</td>
<td>0.050***</td>
<td>0.070***</td>
<td>0.027***</td>
<td>0.092***</td>
<td>0.022***</td>
</tr>
</tbody>
</table>

Note: See Notes to Table 1; $D_i, i=1, 2$ correspond to a value of 1 when the rolling $t$-statistics of $\alpha_2 \leq -1.645$ and $-1.96$, respectively. The parameters of the model estimated is: $Pr(D_i=1|X) = \beta_0 + \beta_1 EMVID$; ***, and ** significant at 1%, and 5% levels, respectively.
Figure 1: Plot of the EMVID Index.
Figure 2: Rolling-window Herding Coefficients.

Note: The horizontal lines with short dashes represent a 10% significance level, while the long dashed lines represent a 5% significance level.