Does war spread herding effect in stock markets? Evidence from emerging and developed markets during the Russia-Ukraine war.

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Abstract

This paper analyzes the impact of the conflict between Russia and Ukraine on the herding behavior observed in international financial markets. Markets belonging to the MSCI World (23 countries) and MSCI Emerging (24 countries) indexes are studied, in addition to Russia, assessing the existence of imitation in the period prior to the invasion, the period immediately after the start of the war and, finally, an extended war period. The sample allows us to analyze the existence of differences between countries geographically close to or far from the conflict, as well as between developed and emerging markets. Additionally, the existence of relationships between the Russian market and herding in the rest (spillovers) and the impact that the war may have had on said relationships is studied. The results indicate that, in general, herding can only be found at the beginning of the war in emerging markets subject to a greater GPR due to their proximity to the conflict or in countries with commercial interests in energy markets. Regarding relationships between markets, the Russian market has seen its influence on other markets limited since the outbreak of the war.

Keywords: herding; CSAD; Russia-Ukraine war; MSCI Emerging; MSCI World.

JEL Codes: G15, G14, G4

1. Introduction

On February 24, 2022, after several months of great uncertainty, the Russian army entered Ukraine, starting an armed conflict that is still active. This confrontation has caused a notable increase in geopolitical risk (GPR) in international financial markets, in addition to having affected the global economy, in part due to a significant increase in uncertainty. Financial literature has documented the negative impact of GPR on markets (Bilson, Brailsford and Hooper, 2002; Choi, 2022; Dimic, Orlov and Piljak, 2015). The negative evolution of the markets in periods of high GPR could be related to the link observed between emotions and the herding behavior of agents in the case of Black Swan type events[1], mainly through market sentiment (Blasco, Corredor and Ferreruela, 2012b;

[1] A Black Swan, according to the theory developed by Taleb (2007), is an extremely rare and unpredictable event that can have a very strong impact on the immediate present. The war in Ukraine is considered a

Economou, Hassapis and Philippas, 2018; Hwang, Rubesam and Salmon, 2021; Liao, Huang and Wu, 2011; Simões Vieira and Valente Pereira, 2015). Behavioral finance suggests that intense emotional reactions, such as panic, fear, euphoria or greed could lead them to make irrational decisions or decisions contrary to their interests.

Said herding behavior is one of the best-known psychological phenomena, and its appearance has been detected in times of special upheaval in the markets, such as financial crises or the COVID-19 pandemic, contributing to destabilize markets (BenMabrouk and Litimi, 2018; Chiang and Zheng, 2010; Kim and Wei, 2002; Mobarek, Mollah and Keasey, 2014). In this sense, and given the negative impact of the Russian-Ukrainian war observed on the financial markets (Boungou and Yatié, 2022) and the global economy (Liadze et al., 2022), we analyze whether the outbreak of the conflict has had implications for the behavior of investors in international financial markets.

Furthermore, herding is not a strictly local phenomenon, but the existence of co-movements or significant relationships between the dynamics of returns in two markets has been observed (Chiang and Zheng, 2010). In the context of the conflict between Russia and Ukraine, it has been observed that the relationship between some markets and financial assets has changed, with the existing interconnection between several of them being notably affected (Umar et al., 2022). This fact leads us to wonder whether the cross-sectional dispersion in each market can be partly explained by the cross-sectional dispersion in the Russian market, and whether these relationship have been affected by the increase in GPR due to the war.

This paper aims to contribute to the branch of literature dedicated to the study of imitative behavior in high GPR situations. The large sample used, which includes both developed and emerging markets, as well as both geographically close to the conflict and also very distant markets, allows us to draw robust and generalizable conclusions. Specifically, the sample includes the main markets of the countries belonging to the MSCI World and MSCI Emerging indexes, to which the Russian market[2] has also been added.

Black Swan because, beyond geopolitical tensions, invasion by Russia was not considered a real possibility until it finally occurred.

[2] Russia was part of the MSCI Emerging index until the start of the conflict.

To our knowledge, this is the first study that analyzes the imitative behavior of investors internationally in this turbulent period, also evaluating the existence of interrelationships between markets. The study of this effect is of interest to managers and regulators, since its presence could affect the diversification and risk management strategies applied, reducing their effectiveness. The rest of the paper is organized as follows: section 2 reviews the previous literature on both the effects of wars on financial markets and the herding effect; section 3 describes the data, section 4 presents the methodology used and the results obtained and, finally, section 5 concludes.

2. Literature review

2.1 Impact of the Russia-Ukraine war on financial markets

Despite being a recent conflict, numerous authors have analyzed the impact of the Russian-Ukrainian war on international financial markets from multiple perspectives. One of the reasons could be that, compared to other geopolitical conflicts, the conflict between Russia and Ukraine is having a larger impact on the global economy (Liadze et al., 2022). Boungou and Yatié (2022) document a negative relationship between war and profitability in global stock markets. These results are in line with those of Ahmed, Hasan and Kamal (2022); Boubaker et al. (2022, 2023); Yousaf, Patel and Yarovaya (2022), or Kamal, Ahmed and Hasan, (2023). Bougias, Episcopos and Leledakis (2022), in the same vein, observe that the war has led to lower prices and greater volatility. The negative impact seems widespread except for energy companies (Nerlinger and Utz, 2022). Gaio et al. (2022) investigate the impact on market efficiency in six developed countries, rejecting the efficiency hypothesis in times of instability. Qureshi et al. (2022) conclude that the risk increased beyond the Russian and Ukrainian borders. Umar et al.(2022) study the interconnection of European markets during the war, concluding that the relationship between them has changed with the arrival of the conflict. Bossman, Gubareva and Teplova (2023) observe the impact of geopolitical risk (GPR) on currencies.

Energy and commodity markets, as well as their relationship with capital markets, have received special attention (Wang et al., 2022; Umar, Riaz and Yousaf, 2022; Fang and Shao, 2022; Fiszeder and Małecka, 2022; Lo et al., 2022; Mohamad, 2022). Diaconaşu, Mehdian and Stoica (2022) investigate the effects of the invasion on global commodity and capital markets, concluding that the only asset that could be considered a

refuge after the start of the conflict would have been oil. Adekoya et al. (2022) study the relationship between oil and other assets such as bonds, stocks or cryptocurrencies, finding a greater connection during than before the war.

2.2 Herding effect in financial markets. Brief review of the literature.

Herding or imitative behavior is said to exist in a market when investors decide to trade following either the transactions of those they consider to be better informed, or the market consensus, instead of following their own information or beliefs (Blasco et al., 2012) [3]. Regarding the detection of the herding effect, in general we can speak of two large categories of measures: on the one hand, those that study imitative behavior among institutional investors and analysts using microdata (Lakonishok, Shleifer and Vishny, 1992; Sias, 2004); on the other hand, those that seek to detect and measure herding behavior defined as trading following market consensus. Within this second group, the measures have been based on the use of aggregate data, the best known being those proposed by Christie and Huang (1995) and Chang, Cheng and Khorana (2000), who study the cross-sectional dispersion of returns. The measure proposed by Hwang and Salmon (2004) also belongs to this second subgroup and is based on the idea that the existence of imitative behavior in a market will cause changes in the CAPM betas of the assets. The empirical results are mixed in both groups of measures, the detection or not of the effect depending on the countries and periods analyzed.

The evidence is inconclusive regarding the impact of financial crises and other particularly turbulent periods on investor behavior. While some studies conclude that herding increases during periods of stress (e.g. BenMabrouk and Litimi, 2018; Chiang and Zheng, 2010; Kim and Wei, 2002; Mobarek, Mollah and Keasey, 2014), others have observed a decrease in the herding behavior in these periods (Choe, Kho and Stulz, 1999; Hwang and Salmon, 2004; Andrikopoulos et al., 2017; Bekiros et al., 2017; Ferreruela and Mallor, 2021).

It has also been observed that this herding behavior can spread from one market to another. The influence of the returns in one market on the behavior of investors in

[3] This section aims to present the herding phenomenon in a general way, rather than carrying out an exhaustive review of all the works published in this field. To expand the information, it is recommended to consult recent bibliometric compilations and analyses, such as those by Spyrou (2013); Kallinterakis and Gregoriou (2017) o Choijil et al. (2022).

another market has been the subject of analysis in several works (Chiang and Zheng, 2010; Economou, Kostakis and Philippas, 2011; Mobarek et al., 2014; Economou et al., 2015; Galariotis, Rong and Spyrou, 2015; Andrikopoulos et al., 2017; Yasir and Önder, 2022). In general, these studies provide information on the existence and dynamics of relationships between returns and herding behavior in different financial markets, highlighting the interconnection between them during various periods, including several crises.

However, the effect that an increase in the GPR may have on investor behavior has hardly been evaluated. The invasion of Ukraine by Russia, with a notable initial impact on the global economy, represents an appropriate scenario to analyze how GPR can affect the behavior of investors.

3. Database

The analysis includes, on the one hand, the main markets of the 23 developed countries that are part of the MSCI World Index (Canada and the United States in America; Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Israel, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom in the Europe and Middle East area; and, finally, Australia, Hong Kong, Japan, New Zealand and Singapore in the Asia-Pacific area). On the other hand, the 24 countries included in the MSCI Emerging Markets Index have been considered (Brazil, Chile, Colombia, Mexico and Peru in America; Czech Republic, Egypt, Greece, Hungary, Kuwait, Poland, Qatar, Saudi Arabia, South Africa, Turkey and the United Arab Emirates in Europe, the Middle East and Africa; and, finally, China, India, Indonesia, South Korea, Malaysia, the Philippines, Taiwan and Thailand in the Asia-Pacific area). Additionally, Russia, which was excluded from the MSCI Emerging index in 2022 as a result of the conflict, has been included in the study.

A database free of survivorship bias has been built by compiling the daily closing prices of the assets traded in the aforementioned stock markets for the period between January 2021 and February 2023. The prices have been obtained from the Refinitiv Datastream database. To avoid problems arising from the inclusion of extremely illiquid assets, those assets that have not been traded in at least 15% of the sessions in which they were “live” in the market have been eliminated from the sample. These assets, due to their

lower trading frequency, can artificially modify the cross-sectional dispersion of returns, decreasing it on the days in which they are not traded (the majority) and increasing it on the days in which they are exchanged in the market.

4. Methodology and results

4.1 Herding towards the market consensus

The measure we use to detect the presence of imitative behavior towards the market consensus is the one proposed by Chang et al. (2000), based on the cross-sectional absolute deviation of returns (CSAD). The intuition underlying this measure is that a low dispersion of individual returns around the average market return indicates that market participants follow correlated trading patterns around said return, considering it as a proxy for the market consensus. The measure is defined as follows:

$$CSAD_{j,t} = \frac{1}{N}\sum_{i=1}^{N} \left|R_{i,j,t} - R_{m,j,t}\right| \quad (1)$$

where N is the number of assets in market *j* on day *t*, $R_{i,j,t}$ is the return on asset *i* on day *t*, and $R_{m,j,t}$ is the simple average of the return of the N assets listed on market *j* on day *t*[4].

The authors argue that, according to standard asset pricing models, the relationship between CSAD and market returns should be linear and increasing. However, if investors follow the market consensus, this relationship would become non-linear and could even become decreasing. For this reason, they use a nonlinear specification that includes a parameter that captures nonlinearities in the relationship between CSAD and market returns:

$$CSAD_{j,t} = \beta_0 + \beta_1\left|R_{m,j,t}\right| + \beta_2 R_{m,j,t}^2 + \varepsilon_t \quad (2)$$

where $R_{m,j,t}$ is the average return of market *j* on day *t,* and ε_t is the error term of the model for day *t*. In the case of herding towards the market consensus, $\beta_2$will take negative and significantly different from 0 values, indicating that CSAD no longer has a positive linear relationship with returns.

[4] Tables 1 and 2 respectively collect the descriptive statistics of the individual series of *Rm* and CSAD, of the set of countries in the MSCI World index and of those belonging to the MSCI Emerging, together with Russia

We estimate the model included in equation (2) for each country for different subperiods[5]. The first subperiod ranges between January 2021 and February 23, 2022[6], and is considered the period before the invasion; the second, between February 24 and May 9, begins the day Russian troops entered Ukraine and lasts until the annual so-called Victory Day in Russia, then considered a key date to notably change the course of the war, creating expectations on the possibility of a Russian announcement of some victory or significant Russian progress at war; finally, the third subperiod runs from April 24, 2022 to February 2023, and corresponds to an extended war period, since the conflict is still active. Both the second and third subperiods include months in which the conflict was in force, however, it has been considered relevant to distinguish between the initial moment of the war, with greater volatility and uncertainty in the markets, and the subsequent period, which we have called "extended war", in which, although the conflict is still active, it no longer represents an unexpected novelty. In this sense, Izzeldin et al. (2023) point out that the response of market volatility to the war was instantaneous, which could indicate that, despite the prolonged period in which Russian troops had been gathered near the border with Ukraine, the real possibility of the invasion had not been discounted by the markets, being considered unlikely until it materialized.

Table 3 shows the results of estimating equation (2) for the MSCI World countries. Among developed markets, negative coefficients are only detected in Canada, New Zealand, Singapore, the United Kingdom and Italy. In the first three, herding disappears in the initial period of the war, indicating that at those times investors would stop following the market consensus and would choose to base their investment decisions on their own information and beliefs. This result is consistent with Ferreruela and Mallor (2021), who observe how imitative behavior disappears in turbulent periods such as the 2008 Global Financial Crisis and the COVID-19 pandemic. The results corresponding to Italy show, however, the existence of herding during the two periods of war, the initial one and the extended war period. At this point it is important to note that United Kingdom and Italy are the two biggest importers (together with Netherlands, which also changes its herding behaviour at the beginning of the war) of Russian energy in Europe.

[5] We adopt the ordinary least squares (OLS) procedure of estimation using heteroskedasticity-consistent standard errors. Lags of the dependent variable (typically one) have also been included if required by the regression process.

[6] The Moscow market was closed between February 28 and March 24, 2022, due to the exacerbated volatility caused by international sanctions imposed on Russia following the invasion.

Particularly, during the period 2020-2021, Italy increased the imports from Russia by 82,6%[7].

The estimation results for the MSCI Emerging countries and Russia are shown in table 4. In line with previous literature, herding behavior is much more widespread in this group (11 of the 25 show significantly negative β_2 coefficients in at least one subperiod) than in developed markets. In some Latin-American markets, herding is detected before the war, but imitative behavior disappears during the initial period of the war. However, in the Czech Republic, Hungary, Poland and Turkey, the markets in the sample which are geographically closest to the conflict, herding appears and even extends during the extended war period. This could indicate that GPR has a relevant role in the behavior of investors in financial markets. Their geographical proximity and, therefore, historical connections and political interactions lead these nations to have overlapping geopolitical interests, leading to alliances or conflicts due to territorial claims, power struggles, or regional dominance. But they have also had cultural exchanges, trade relationships, and migrations between them, influencing each other's languages, traditions, and customs over centuries.

Herding is also observed at the beginning of the war in Kuwait, Qatar and the United Arab Emirates. The results observed in the Middle East region (note that even Saudi Arabia shows a noticeable change although not significant) could be linked to the fact that they are main oil-producing countries with big reserves of gas and, therefore, deeply involved in mitigating the possible export cuts from Russia. These results are in line with Balcilar et al. (2017) and Yousef and Mokni (2023) who find no evidence of herding by investors in the Saudi Arabia stock market, and suggest that the homogeneity of investors in that market could explain that finding (Rahman et al. 2015). The geopolitical balance in this region is complex and commercial interests related to the oil and gas energy markets have great influence on its financial markets.

Finally, we present the results of the Russian market. In this case, herding is detected (consistent with Bougatef and Nejah, 2023) at the beginning of the war (taking

[7] Observatory of Economic Complexity (OEC) https://oec.world/es/profile/country/ita?yearlyTradeFlowSelector=flow1&flowSelector1=flow1 on January 14, 2024.

into account that in this market this period is limited because it remained closed for a month after the start of the invasion), disappearing afterwards.

Given the results, we could say that although herding behavior does exist in several markets studied, there seem to be differences between developed and emerging markets, with a more significant presence of herding behavior in the second group. In general, an increase in herding is not observed in the first months of the war between Russia and Ukraine. On the contrary, several countries in which herding is observed in the previous period do not show evidence of herding behavior during the first months of the conflict. However, there seems to be a relationship between herding behaviour and GPR, since the countries geographically close to the conflict, as well as those emerging markets that are oil producers and can substitute Russian energy products, are the ones that have shown herding during the first months of the invasion.

4.2 Cross-country herding effects.

To conclude the study, we analyze whether the dynamic of returns in the Russian market contributes to explain herding behaviour in other markets. More precisely, we study whether the cross-sectional dispersion in each market can be partly explained by the cross-sectional dispersion in the Russian market and, if so, whether these relationships have been affected by the war. We follow Economou, Kostakis and Philippas (2011) and include one additional term in the model in equation (2): the CSAD of the Russian market. Specifically, we estimate the following regression:

$$CSAD_{j,t} = \beta_0 + \beta_1 \left| R_{m,j,t} \right| + \beta_2 R_{m,j,t}^2 + \beta_3 CSAD_{RUS,t} + \varepsilon_t \qquad (3)$$

where $CSAD_{RUS,t}$ is the CSAD of the Russian market for day t[8]. A positive and significant value of β_3, would mean that the cross-sectional dispersions of returns exhibit a certain degree of co-movement with the Russian market.

Table 5 shows the results of estimating model (3) for the main markets of the countries listed in MSCI World index. Regarding herding behavior, introducing the cross-sectional deviation of the Russian market does not drastically modify the results with regard to the model in equation (2). New Zealand, Singapore and Canada again show significant herding behavior prior to the outbreak of the work, whereas Italy keeps

[8] The time difference between the markets has been considered, introducing the lagged variable ($CSAD_{RUS,t-1}$) in the Asia-Pacific markets.

showing a significant negative coefficient in the extended war period. However, when we consider the Russian influence, Italy no longer shows significant herding levels at the beginning of the conflict. Regarding the influence of the Russian market, 15 significant coefficients are observed in the pre-war period, 11 positive and 4 negative. The number of significant coefficients in the extended war period is slightly lower (12, 9 positive and 3 negative). However, in the first weeks of the conflict, just two significant (positive) coefficients are found. In view of these results, we could say that the cross-sectional dispersion of returns of those markets can be partly explained by the cross-sectional dispersion in the Russian market, and that the influence of the Russian market over the developed markets in the sample almost disappeared following the outbreak of the war, although it has almost completely recovered afterwards.

The results for the markets belonging to the MSCI Emerging index are presented in table 6. In the case of emerging markets, we also found hardly any differences in the herding detected when estimating this model and when estimating the basic model without including the Russian CSAD. Herding behavior is found at the beginning of the war in the bordering countries as well as in those that compete with Russia in the energy markets (with the incorporation of Saudi Arabia). Regarding the influence of the Russian market, in the pre-war period, there were 7 markets which CSAD was significantly related to the Russian one, of which 6 did so inversely (Greece, Kuwait, Saudi Arabia, Indonesia, Taiwan and Thailand, with just Brazil showing a positive coefficient). Nevertheless, the start of the war meant a change in relationships between countries. Those previously related ceased to have a significant influence and were replaced by Egypt, China, Taiwan and Mexico. The dynamics of returns in these markets (with the exception of Mexico) continued to be related (again negatively) to that of the Russian market in the period of extended war.

In view of the results shown in tables 5 and 6, with respect to the Russian market, given the difference between the pre-war period and the extended war period, it could be said that the conflict has had a significant impact on the relationships between Russia and other world markets. That said, certain differences are generally observed between developed and emerging markets. While in the case of the developed ones we could speak of the existence of co-movements (as the significant coefficients are positive), as well as the disappearance of relations at the beginning of the war to recover, although not

completely, in the subsequent phase; in the case of the emerging ones, most of the relationships are of the inverse type, and a change occurs at the beginning of the war with continuity in the subsequent period (in this group there is no return to the pre-war situation).

5. Conclusions

This work analyzes the relationship between GPR and the herd behavior of investors in the context of the Russian-Ukrainian conflict that began in February 2022, using data corresponding to the countries of the MSCI World and MSCI Emerging index, together with Russia. Three subperiods are studied, one prior to the war, one corresponding to the first weeks of the conflict and another one called "extended war", in which the conflict is still active but the impact on financial markets has softened. The measure of Chang et al. (2000) is used to estimate the presence of herding towards the market consensus, additionally analyzing the existence of co-movement between the cross sectional deviation of returns of the Russian market and that of the other markets.

The results indicate that the presence of herding behavior is quite limited in developed markets. Moreover, in cases where it is detected, the arrival of the conflict makes it disappear during the first months. In emerging markets there is a greater presence of herding and, furthermore, in several it continues to be present during the initial phases of the war. Specifically, in those geographically close to the conflict and in oil-producing countries that can be deeply involved in compensating Russian energy export reductions.

With regard to the relationships between the cross-sectional dispersion in each market and the cross-sectional dispersion in the Russian market, we can say that there are also differences between developed and emerging markets, with developed showing mainly positive relationships and emerging being scarcely and negatively related to the Russian market. A key finding of this study is that the co-movement with the Russian market in the cross-sectional returns' dispersion would be limited to developed markets, and not in high GPR times, as the relationships are mainly not significant in the first weeks of the war.

References

Adekoya, O. B., Oliyide, J. A., Yaya, O. S., & Al-Faryan, M. A. S. (2022). Does oil connect differently with prominent assets during war? Analysis of intra-day data during the Russia-Ukraine saga. *Resources Policy*, *77*, 102728. https://doi.org/10.1016/j.resourpol.2022.102728

Ahmed, S., Hasan, M. M., & Kamal, M. R. (2022). Russia–Ukraine crisis: The effects on the European stock market. *European Financial Management*. https://doi.org/10.1111/eufm.12386

Ali-Rind, A., Boubaker, S., & Jarjir, S. L. (2023). Peer effects in financial economics: A literature survey. *Research in International Business and Finance*, *64*, 101873. https://doi.org/https://doi.org/10.1016/j.ribaf.2022.101873

Andrikopoulos, P., Kallinterakis, V., Leite Ferreira, M. P., & Verousis, T. (2017). Intraday herding on a cross-border exchange. *International Review of Financial Analysis*, *53*, 25–36. https://doi.org/https://doi.org/10.1016/j.irfa.2017.08.010

Bekiros, S., Jlassi, M., Lucey, B., Naoui, K., & Uddin, G. S. (2017). Herding behavior, market sentiment and volatility: Will the bubble resume? *North American Journal of Economics and Finance*, *42*, 107–131. https://doi.org/10.1016/j.najef.2017.07.005

BenMabrouk, H., & Litimi, H. (2018). Cross herding between American industries and the oil market. *North American Journal of Economics and Finance*, *45*, 196–205. https://doi.org/10.1016/j.najef.2018.02.009

Bilson, C. M., Brailsford, T. J., & Hooper, V. C. (2002). The explanatory power of political risk in emerging markets. *International Review of Financial Analysis*, *11*(1), 1–27. https://doi.org/https://doi.org/10.1016/S1057-5219(01)00067-9

Blasco, N., Corredor, P., & Ferreruela, S. (2012a). Does herding affect volatility? Implications for the Spanish stock market. *Quantitative Finan*, *12*(2), 311–327. https://doi.org/10.1080/14697688.2010.516766

Blasco, N., Corredor, P., & Ferreruela, S. (2012b). Market sentiment: A key factor of investors' imitative behaviour. https://doi.org/10.1111/j.1467-629X.2011.00412.x

Bossman, A., Gubareva, M., & Teplova, T. (2023). Asymmetric effects of geopolitical risk on major currencies: Russia-Ukraine tensions. *Finance Research Letters*, *51*, 103440. https://doi.org/10.1016/j.frl.2022.103440

Boubaker, S., Goodell, J. W., Pandey, D. K., & Kumari, V. (2022). Heterogeneous impacts of wars on global equity markets: Evidence from the invasion of Ukraine. *Finance Research Letters*, *48*, 102934. https://doi.org/10.1016/j.frl.2022.102934

Boubaker, S., Nguyen, N., Trinh, V. Q., & Vu, T. (2023). Market reaction to the Russian Ukrainian war: a global analysis of the banking industry. *Review of Accounting and Finance*, *22*(1), 123–153. https://doi.org/10.1108/RAF-10-2022-0294

Bougatef, K., & Nejah, I. (2023). Does Russia–Ukraine war generate herding behavior in Moscow Exchange? *Review of Behavioral Finance*, *ahead-of-p*(ahead-of-print). https://doi.org/10.1108/RBF-01-2023-0014

Bougias, A., Episcopos, A., & Leledakis, G. N. (2022). Valuation of European firms during the Russia–Ukraine war. *Economics Letters*, *218*, 110750. https://doi.org/10.1016/j.econlet.2022.110750

Boungou, W., & Yatié, A. (2022). The impact of the Ukraine–Russia war on world stock market returns. *Economics Letters*, *215*, 110516. https://doi.org/10.1016/j.econlet.2022.110516

Chang, E., Cheng, J., & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking and Finance*, *2000*. Retrieved from http://linkinghub.elsevier.com/retrieve/pii/S0378426699000965

Chiang, T. C., & Zheng, D. (2010a). An empirical analysis of herd behavior in global stock markets. *Journal of Banking & Finance*, *34*(8), 1911–1921. https://doi.org/10.1016/j.jbankfin.2009.12.014

Chiang, T. C., & Zheng, D. (2010b). An empirical analysis of herd behavior in global stock markets. *Journal of Banking & Finance*, *34*(8), 1911–1921. https://doi.org/https://doi.org/10.1016/j.jbankfin.2009.12.014

Choe, H., Kho, B.-C., & Stulz, R. M. (1999). Do foreign investors destabilize stock markets? The Korean experience in 1997. *Journal of Financial Economics*, *54*(2), 227–264. https://doi.org/https://doi.org/10.1016/S0304-405X(99)00037-9

Choi, S.-Y. (2022). Evidence from a multiple and partial wavelet analysis on the impact of geopolitical concerns on stock markets in North-East Asian countries. *Finance Research Letters*, *46*, 102465. https://doi.org/https://doi.org/10.1016/j.frl.2021.102465

Choijil, E., Méndez, C. E., Wong, W.-K., Vieito, J. P., & Batmunkh, M.-U. (2022). Thirty years of herd behavior in financial markets: A bibliometric analysis. *Research in International Business and Finance*, *59*, 101506. https://doi.org/https://doi.org/10.1016/j.ribaf.2021.101506

Christie, W. G., & Huang, R. D. (1995). Following the Pied Piper: Do Individual Returns Herd around the Market? *Financial Analysts Journal*, *51*(4), 31–37. https://doi.org/10.2469/faj.v51.n4.1918

Diaconaşu, D. E., Mehdian, S. M., & Stoica, O. (2022). The reaction of financial markets to Russia's invasion of Ukraine: evidence from gold, oil, bitcoin, and major stock markets. *Applied Economics Letters*, 1–5. https://doi.org/10.1080/13504851.2022.2107608

Dimic, N., Orlov, V., & Piljak, V. (2015). The political risk factor in emerging, frontier, and developed stock markets. *Finance Research Letters*, *15*, 239–245. https://doi.org/https://doi.org/10.1016/j.frl.2015.10.007

Economou, F., Hassapis, C., & Philippas, N. (2018). Investors' fear and herding in the stock market. *Applied Economics*, *50*(34–35), 3654–3663. https://doi.org/10.1080/00036846.2018.1436145

Economou, F., Kostakis, A., & Philippas, N. (2011). Cross-country effects in herding behaviour: Evidence from four south European markets. *Journal of International Financial Markets, Institutions and Money*, *21*(3), 443–460. https://doi.org/10.1016/j.intfin.2011.01.005

Fang, Y., & Shao, Z. (2022). The Russia-Ukraine conflict and volatility risk of commodity markets. *Finance Research Letters*, *50*, 103264. https://doi.org/10.1016/j.frl.2022.103264

Ferreruela, S., & Mallor, T. (2021). Herding in the bad times: The 2008 and COVID-19 crises. *The North American Journal of Economics and Finance*, *58*, 101531. https://doi.org/https://doi.org/10.1016/j.najef.2021.101531

Fiszeder, P., & Małecka, M. (2022). Forecasting volatility during the outbreak of Russian invasion of Ukraine: application to com-modities, stock indices, currencies, and cryptocurrencies. *Equilibrium*, *17*(4), 939–967. https://doi.org/10.24136/eq.2022.032

Gaio, L. E., Stefanelli, N. O., Pimenta, T., Bonacim, C. A. G., & Gatsios, R. C. (2022). The impact of the Russia-Ukraine conflict on market efficiency: Evidence for the developed stock market. *Finance Research Letters*, *50*, 103302.

https://doi.org/10.1016/j.frl.2022.103302

Galariotis, E. C., Rong, W., & Spyrou, S. I. (2015). Herding on fundamental information: A comparative study. *Journal of Banking & Finance*, *50*, 589–598. https://doi.org/https://doi.org/10.1016/j.jbankfin.2014.03.014

Hwang, S., Rubesam, A., & Salmon, M. (2021). Beta herding through overconfidence: A behavioral explanation of the low-beta anomaly. *Journal of International Money and Finance*, *111*, 102318. https://doi.org/10.1016/j.jimonfin.2020.102318

Hwang, S., & Salmon, M. (2004). Market stress and herding. *Journal of Empirical Finance*, *11*(4), 585–616. https://doi.org/10.1016/j.jempfin.2004.04.003

Izzeldin, M., Muradoğlu, Y. G., Pappas, V., Petropoulou, A., & Sivaprasad, S. (2023). The impact of the Russian-Ukrainian war on global financial markets. *International Review of Financial Analysis*, *87*, 102598. https://doi.org/https://doi.org/10.1016/j.irfa.2023.102598

Kallinterakis, & Gregoriou, G. N. (2017). Herd behaviour: A survey. *AESTIMATIO : The IEB International Journal of Finance*, 8–25.

Kamal, M. R., Ahmed, S., & Hasan, M. M. (2023). The impact of the Russia-Ukraine crisis on the stock market: Evidence from Australia. *Pacific-Basin Finance Journal*, *79*, 102036. https://doi.org/https://doi.org/10.1016/j.pacfin.2023.102036

Kim, W., & Wei, S.-J. (2002). Foreign portfolio investors before and during a crisis. *Journal of International Economics*, *56*(1), 77–96. https://doi.org/https://doi.org/10.1016/S0022-1996(01)00109-X

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1992). The Impact of Institutional Trading on Stock Prices. *Journal of Financial Economics*, *32*(1).

Liadze, I., Macchiarelli, C., Mortimer-Lee, P., & Sanchez Juanino, P. (2022). Economic costs of the Russia-Ukraine war. *The World Economy*. https://doi.org/10.1111/twec.13336

Liao, T. L., Huang, C. J., & Wu, C. Y. (2011). Do fund managers herd to counter investor sentiment? *Journal of Business Research*, *64*(2), 207–212. https://doi.org/10.1016/j.jbusres.2010.01.007

Lo, G.-D., Marcelin, I., Bassène, T., & Sène, B. (2022). The Russo-Ukrainian war and financial markets: the role of dependence on Russian commodities. *Finance Research Letters*, *50*, 103194. https://doi.org/10.1016/j.frl.2022.103194

Mobarek, A., Mollah, S., & Keasey, K. (2014). A cross-country analysis of herd behavior in Europe. *Journal of International Financial Markets, Institutions and Money*, *32*(1), 107–127. https://doi.org/10.1016/j.intfin.2014.05.008

Mohamad, A. (2022). Safe flight to which haven when Russia invades Ukraine? A 48-hour story. *Economics Letters*, *216*, 110558. https://doi.org/10.1016/j.econlet.2022.110558

Nerlinger, M., & Utz, S. (2022). The impact of the Russia-Ukraine conflict on energy firms: A capital market perspective. *Finance Research Letters*, *50*, 103243. https://doi.org/10.1016/j.frl.2022.103243

Qureshi, A., Rizwan, M. S., Ahmad, G., & Ashraf, D. (2022). Russia–Ukraine war and systemic risk: Who is taking the heat? *Finance Research Letters*, *48*, 103036. https://doi.org/10.1016/j.frl.2022.103036

Sias, R. W. (2004). Institutional Herding. *The Review of Financial Studies*, *17*(1), 165–206. Retrieved from http://www.jstor.org/stable/1262672

Simões Vieira, E. F., & Valente Pereira, M. S. (2015). Herding behaviour and sentiment:

Evidence in a small European market. *Revista de Contabilidad-Spanish Accounting Review*, *18*(1), 78–86. https://doi.org/10.1016/j.rcsar.2014.06.003

Spyrou, S. (2013). Herding in financial markets: A review of the literature. *Review of Behavioral Finance*, *5*(2), 175–194. https://doi.org/10.1108/RBF-02-2013-0009

Taleb, N. N. (2007). *The black swan: The impact of the highly improbable* (Vol. 2). Random house.

Umar, M., Riaz, Y., & Yousaf, I. (2022). Impact of Russian-Ukraine war on clean energy, conventional energy, and metal markets: Evidence from event study approach. *Resources Policy*, *79*, 102966. https://doi.org/10.1016/j.resourpol.2022.102966

Umar, Z., Polat, O., Choi, S.-Y., & Teplova, T. (2022). The impact of the Russia-Ukraine conflict on the connectedness of financial markets. *Finance Research Letters*, *48*, 102976. https://doi.org/10.1016/j.frl.2022.102976

Wang, Y., Bouri, E., Fareed, Z., & Dai, Y. (2022). Geopolitical risk and the systemic risk in the commodity markets under the war in Ukraine. *Finance Research Letters*, *49*, 103066. https://doi.org/10.1016/j.frl.2022.103066

Yasir, M., & Önder, A. Ö. (2022). Time-varying herding spillover for emerging countries: evidence from BRIC countries and Turkey. *Review of Behavioral Finance*, *ahead-of-p*(ahead-of-print). https://doi.org/10.1108/RBF-10-2021-0218

Yousaf, I., Patel, R., & Yarovaya, L. (2022). The reaction of G20+ stock markets to the Russia–Ukraine conflict "black-swan" event: Evidence from event study approach. *Journal of Behavioral and Experimental Finance*, *35*. https://doi.org/10.1016/j.jbef.2022.100723

Tables

Table 1. *Descriptive statistics*. *MSCI World*.

	Market return				CSAD				
	Mean	Max.	Min.	S.D.	Mean	Max.	Min.	S.D.	N
Austria	0.0003	0.0380	-0.0365	0.0071	0.0142	0.0363	0.0062	0.0041	511
Belgium	-0.0001	0.0304	-0.0285	0.0066	0.0136	0.0260	0.0073	0.0028	517
Denmark	-0.0001	0.0263	-0.0339	0.0080	0.0200	0.0329	0.0121	0.0037	505
Finland	-0.0002	0.0427	-0.0548	0.0094	0.0154	0.0249	0.0103	0.0026	507
France	-0.0002	0.0377	-0.0366	0.0068	0.0188	0.0384	0.0116	0.0031	517
Germany	-0.0003	0.0431	-0.0477	0.0088	0.0172	0.0372	0.0000	0.0031	515
Ireland	0.0005	0.0374	-0.0334	0.0087	0.0189	0.0441	0.0002	0.0062	518
Italy	0.0002	0.0431	-0.0509	0.0079	0.0151	0.0300	0.0105	0.0027	514
Netherlands	0.0001	0.0427	-0.0361	0.0085	0.0139	0.0297	0.0072	0.0032	517
Norway	-0.0001	0.0318	-0.0503	0.0088	0.0210	0.0400	0.0148	0.0031	507
Portugal	0.0009	0.0256	-0.0328	0.0074	0.0157	0.0377	0.0056	0.0052	517
Spain	0.0000	0.0212	-0.0278	0.0061	0.0138	0.0271	0.0078	0.0026	515
Sweden	-0.0004	0.0370	-0.0511	0.0102	0.0234	0.0341	0.0175	0.0032	508
Switzerland	-0.0001	0.0324	-0.0301	0.0072	0.0133	0.0279	0.0087	0.0026	509
United Kingdom	-0.0003	0.0232	-0.0380	0.0067	0.0186	0.0367	0.0130	0.0029	504
Israel	-0.0007	0.0274	-0.0392	0.0085	0.0166	0.0376	0.0121	0.0023	488
Australia	0.0004	0.0219	-0.0573	0.0092	0.0300	0.0472	0.0212	0.0035	506
Hong Kong	0.0000	0.0414	-0.0419	0.0082	0.0237	0.0501	0.0154	0.0039	491
Japan	0.0000	0.0313	-0.0283	0.0083	0.0132	0.0250	0.0094	0.0022	489
New Zealand	-0.0003	0.0117	-0.0230	0.0045	0.0136	0.0216	0.0084	0.0022	500
Singapore	0.0005	0.0160	-0.0210	0.0048	0.0154	0.0261	0.0074	0.0028	502
Canada	0.0010	0.0293	-0.0476	0.0093	0.0399	0.0610	0.0262	0.0058	502
United States	0.0001	0.0508	-0.0469	0.0126	0.0161	0.0344	0.0000	0.0037	509

Table 2. *Descriptive statistics*. *MSCI Emerging + Russia*.

	Market return				CSAD				
	Mean	Max.	Min.	S.D.	Mean	Max.	Min.	S.D.	N
Czech Republic	0.0008	0.0408	-0.0546	0.0093	0.0120	0.0784	0.0019	0.0108	505
Greece	0.0010	0.0469	-0.0642	0.0089	0.0165	0.0329	0.0077	0.0033	499
Hungary	-0.0001	0.0444	-0.0670	0.0088	0.0154	0.0408	0.0057	0.0053	506
Poland	0.0004	0.0498	-0.0841	0.0076	0.0238	0.0534	0.0172	0.0040	504
Turkey	0.0018	0.0550	-0.0947	0.0159	0.0212	0.0393	0.0082	0.0042	502
Kuwait	0.0008	0.0229	-0.0303	0.0062	0.0153	0.0332	0.0074	0.0044	491
Qatar	-0.0001	0.0443	-0.0336	0.0071	0.0110	0.0304	0.0040	0.0037	498
Saudí Arabia	-0.0001	0.0252	-0.0486	0.0083	0.0123	0.0241	0.0069	0.0027	498
UAE	0.0010	0.0246	-0.0414	0.0067	0.0160	0.0376	0.0042	0.0051	502
Egypt	0.0005	0.0360	-0.0670	0.0128	0.0189	0.0496	0.0081	0.0055	488
South Africa	0.0010	0.0173	-0.0264	0.0061	0.0200	0.0323	0.0126	0.0032	501
China	0.0006	0.0406	-0.0676	0.0118	0.0178	0.0290	0.0107	0.0026	481
India	0.0020	0.0208	-0.0349	0.0064	0.0247	0.0337	0.0174	0.0027	497
Indonesia	0.0005	0.0159	-0.0206	0.0053	0.0214	0.0300	0.0150	0.0028	494
Korea	0.0000	0.0379	-0.0487	0.0116	0.0152	0.0249	0.0105	0.0024	494
Malaysia	0.0003	0.0342	-0.0321	0.0072	0.0198	0.0360	0.0140	0.0028	487
Philippines	-0.0001	0.0156	-0.0354	0.0065	0.0168	0.0305	0.0102	0.0031	494
Taiwan	0.0006	0.0592	-0.0543	0.0112	0.0137	0.0333	0.0081	0.0033	484
Thailand	0.0008	0.0253	-0.0326	0.0075	0.0158	0.0287	0.0102	0.0031	483
Brazil	-0.0007	0.0244	-0.0351	0.0104	0.0176	0.0328	0.0114	0.0034	500
Chile	-0.0002	0.0751	-0.0699	0.0090	0.0130	0.0345	0.0071	0.0035	501
Colombia	-0.0004	0.0412	-0.0283	0.0080	0.0132	0.0368	0.0038	0.0054	492
Mexico	0.0003	0.0142	-0.0162	0.0048	0.0126	0.0253	0.0076	0.0025	507
Peru	0.0005	0.0537	-0.0651	0.0095	0.0137	0.0556	0.0026	0.0069	504
Russia	0.0004	0.1309	-0.1809	0.0154	0.0156	0.0822	0.0086	0.0069	490

Table 3. *Estimates of herding in the different subperiods. MSCI World.*

	Pre-war	*War*	*Extended war*
Austria	0.7205	3.4945	6.3681
	(0.2505)	(1.0732)	(0.8121)
Belgium	5.7550***	11.9673***	-0.3587
	(2.6674)	(2.8295)	(-0.0718)
Denmark	-1.4435	-0.2325	5.9707
	(-0.6098)	(-0.0382)	(0.9043)
Finland	0.2190	-1.0536	1.1877
	(0.3257)	(-0.5400)	(0.2673)
France	3.7046**	0.1618	2.2148
	(2.0095)	(0.0736)	(1.3196)
Germany	1.5911*	1.2821	-0.0607
	(1.7391)	(0.4986)	(-0.0194)
Ireland	-2.1366	-9.5303	9.3944
	(-0.3482)	(-0.9416)	(1.2929)
Italy	-0.8701	-2.4856*	-8.7203***
	(-0.5563)	(-1.6829)	(-4.9306)
Netherlands	4.4764***	1.0703	0.1100
	(2.5980)	(0.5605)	(0.0603)
Norway	-0.6849	5.6688	6.3859***
	(-0.8988)	(0.6417)	(3.0343)
Portugal	-1.4385	20.4820*	24.8450**
	(-0.1834)	(1.8734)	(2.5731)
Spain	3.1203	-4.8632	-2.5878
	(0.9349)	(-0.6027)	(-0.6616)
Sweden	0.9131	-0.2197	-0.3532
	(1.2531)	(-0.0825)	(-0.1220)
Switzerland	9.3274***	5.0560	-0.5899
	(3.3123)	(1.1293)	(-0.2055)
United Kingdom	-1.1281	-3.3997	-8.1594**
	(-1.0655)	(-0.8536)	(-2.4202)
Israel	-0.6322	-1.3307	-3.0404
	(-0.5051)	(-0.7905)	(-0.9115)
Australia	1.5020	-0.4590	-2.2554
	(0.8610)	(-0.1495)	(-0.7034)
Hong Kong	-0.2533	3.9066	3.5360
	(-0.0960)	(1.0838)	(0.8111)
Japan	4.3453**	-0.3230	14.0783***
	(1.9974)	(-0.0704)	(2.6719)
New Zealand	-9.5354**	2.8008	-5.6333
	(-2.0058)	(0.2902)	(-1.3667)
Singapore	-14.1389*	-4.9090	-4.7600
	(-1.7739)	(-0.6009)	(-0.5735)
Canada	-4.6392***	0.2106	-3.9870
	(-2.6109)	(0.0673)	(-1.0241)
United States	-5.6599	7.5367	2.4245
	(-1.4275)	(1.5528)	(1.0706)

The table shows the results corresponding to the estimation of the model in equation (2) for each of the countries and subperiods studied: $CSAD_{j,t} = \beta_0 + \beta_1 \left| R_{m,j,t} \right| + \beta_2 R_{m,j,t}^2 + \varepsilon_t$. For reasons of space, only the values of β_2 coefficient are shown. This coefficient captures the presence of imitative behavior. The values in parentheses correspond to the t-statistics. *** indicates that the coefficient is significant at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 1% level.

Table 4. *Estimates of herding in the different subperiods. MSCI Emerging + Rusia.*

	Pre-war	*War*	*Extended war*
Russia	-0.1158	-4.9127***	-0.4539
	(-0.2476)	(-4.6760)	(-0.8856)
Czech Republic	4.4029	-12.5848*	12.5056
	(0.8756)	(-1.6913)	(1.1530)
Greece	-4.8521	-0.6236	-4.0302
	(-1.4080)	(-0.8644)	(-1.1840)
Hungary	-11.7501**	-6.2233***	3.7205
	(-2.0807)	(-3.4026)	(0.3519)
Poland	-2.4360***	-0.6343*	3.3779
	(-3.1044)	(-1.7310)	(0.6952)
Turkey	-2.9172***	-3.0094***	-1.2255***
	(-3.5629)	(-5.7937)	(-2.7997)
Kuwait	-15.7905***	-115.9703*	-6.1840**
	(-2.6539)	(-1.8994)	(-1.7413)
Qatar	-0.0622	-45.7799**	2.9545
	(-0.0075)	(-2.5520)	(1.5931)
Saudi Arabia	1.9426*	-3.1993	0.4030
	(2.3863)	(-0.9406)	(0.1880)
UAE	-10.8260*	-22.0255*	-2.4525
	(-1.7601)	(-1.8170)	(-0.9090)
Egypt	5.0727***	-0.6671	4.0966***
	(2.6223)	(-0.5472)	(3.4224)
South Africa	4.6409	-10.4507	16.7717
	(0.8671)	(-1.1870)	(1.3944)
China	0.7163	0.3600	-1.8734
	(0.3019)	(0.4420)	(-1.3051)
India	-4.5855	-3.1230	1.4687
	(-1.2398)	(-1.3143)	(0.4750)
Indonesia	0.9358	11.5815*	-3.5343
	(0.1337)	(1.7304)	(-0.8273)
Korea	0.1339	4.8402	1.7532*
	(0.1151)	(0.9689)	(1.7673)
Malaysia	1.7694	-3.0410	3.3861
	(0.3741)	(-1.3202)	(0.8605)
Philippines	2.6154*	-9.9299	5.2316
	(1.7110)	(-1.5501)	(0.5910)
Taiwan	-1.6884	1.8945	3.9068***
	(-1.1948)	(0.6707)	(3.9981)
Thailand	2.8732	1.2899	5.6562***
	(1.6489)	(0.4633)	(3.8674)
Brazil	1.2620	12.2562***	9.0076***
	(0.6595)	(2.7523)	(3.3162)
Chile	-0.9485	40.0493*	-5.2938*
	(-1.2041)	(1.7570)	(-1.7184)
Colombia	-8.9890***	4.3343	-8.3941
	(-3.5204)	(0.4274)	(-1.2408)
Mexico	8.3440	18.9439*	12.5281
	(1.0824)	(1.8491)	(1.3945)
Peru	-3.8428**	-4.5175	-20.3475*
	(-2.3600)	(-1.6129)	(-1.7561)

The table shows the results corresponding to the estimation of the model in equation (2) for each of the countries and subperiods studied: : $CSAD_{j,t} = \beta_0 + \beta_1 \left| R_{m,j,t} \right| + \beta_2 R_{m,j,t}^2 + \varepsilon_t$. For reasons of space, only the values of the β_2 coefficients are shown. This coefficient captures the presence of imitative behavior. The values in parentheses correspond to the t-statistics. *** indicates that the coefficient is significant at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 1% level.

Table 5. *Estimates of herding incorporating Russia's CSAD. MSCI World.*

	Pre-war		*War*		*Extended war*	
	$R^2_{m,j}$	$CSAD_{RUS}$	$R^2_{m,j}$	$CSAD_{RUS}$	$R^2_{m,j}$	$CSAD_{RUS}$
Austria	-2.2530	0.1001**	6.3653	0.0304	5.2422	0.0370
	(-0.7494)	(2.5808)	(1.0183)	(0.7070)	(0.6563)	(0.5162)
Belgium	5.2962**	0.0767***	18.7064***	-0.0018	2.9161	0.0934**
	(2.3410)	(2.6242)	(2.9962)	(-0.0709)	(0.5716)	(2.0188)
Denmark	-2.9226	0.1110***	12.0206**	-0.0070	4.9945	0.0857**
	(-1.2669)	(2.6938)	(2.1926)	(-0.4270)	(0.8589)	(2.0346)
Finland	0.1107	0.0848***	0.5481	-0.0295	-3.2659	0.0389
	(0.1630)	(3.0181)	(0.1804)	(-1.3145)	(-0.6773)	(1.3608)
France	2.9397*	0.0412*	-0.3276	0.0339**	6.1516	0.0808**
	(1.6594)	(1.6511)	(-0.1165)	(2.1814)	(1.3546)	(2.4743)
Germany	2.1989***	0.0153	-3.0418	0.0211	3.9789	0.0234
	(2.9817)	(0.7926)	(-0.5916)	(1.0679)	(0.9951)	(0.7154)
Ireland	1.5010	-0.1679***	7.8618	0.0164	6.1687	0.0766
	(0.2351)	(-2.8806)	(0.3417)	(0.2953)	(0.8058)	(0.8710)
Italy	-1.0024	0.0471**	0.8809	0.0269	-7.5846***	0.0805**
	(-0.6675)	(2.3895)	(0.3791)	(1.2626)	(-5.1247)	(2.5351)
Netherlands	3.5652*	0.0669**	4.0228	-0.0061	1.9593	0.0967**
	(1.9429)	(2.2140)	(0.6112)	(-0.2723)	(0.9187)	(2.3252)
Norway	-0.9933	0.0620**	6.6023	0.0218	6.2887**	0.0660
	(-1.3561)	(2.0679)	(0.8633)	(0.8509)	(2.2674)	(1.5710)
Portugal	-1.1632	-0.0013	11.2709	0.0222	33.1879***	0.2990***
	(-0.1442)	(-0.0154)	(0.7811)	(0.3829)	(2.8567)	(3.3388)
Spain	2.9739	-0.0433*	4.9312	0.0037	-0.3078	-0.0273
	(0.9132)	(-1.8669)	(0.3494)	(0.1815)	(-0.0659)	(-0.8454)
Sweden	0.1449	0.1255***	2.8372	-0.0060	-0.8412	0.0873**
	(0.2020)	(4.3886)	(0.7667)	(-0.2839)	(-0.2622)	(2.0659)
Switzerland	8.1968***	0.0680**	40.1447***	-0.0059	1.9712	0.0760*
	(2.9969)	(2.5842)	(6.0920)	(-0.5068)	(0.7016)	(1.9202)
United Kingdom	-0.9519	0.0100	0.8791	0.0415	-5.6405	0.0840***
	(-0.9150)	(0.5112)	(0.2033)	(1.6881)	(-1.4967)	(2.6938)
Israel	-0.9062	-0.0325	-1.9250	0.0324*	-1.6926	-0.0226
	(-0.5596)	(-1.5520)	(-0.9092)	(1.8003)	(-0.4358)	(-0.6113)
Australia	1.7260	-0.0396	2.9131	0.0365	-1.0569	-0.1681***
	(0.9658)	(-1.1896)	(0.4767)	(1.2270)	(-0.3325)	(-4.3253)
Hong Kong	-1.3159	-0.0858***	-5.3249	0.0148	2.9464	-0.0866*
	(-0.5421)	(-4.0561)	(-0.8090)	(0.8308)	(0.6719)	(-1.9508)
Japan	4.4869**	-0.0060	38.7199	0.0348	13.4333***	-0.0456
	(2.0533)	(-0.3076)	(1.4825)	(1.0220)	(2.6490)	(-1.2758)
New Zealand	-10.7494**	0.0434*	0.3569	0.0144	-4.3034	0.0394
	(-2.3130)	(1.6855)	(0.0428)	(0.5049)	(-1.0201)	(0.9240)
Singapore	-14.5876*	-0.0569**	24.5225	0.0368	-1.5040	-0.1315***
	(-1.8350)	(-2.0721)	(0.2128)	(1.6561)	(-0.2113)	(-3.8456)
Canada	-4.3292**	0.0528	-3.8344	0.0139	0.2318	-0.0481
	(-2.3598)	(1.1223)	(-0.3059)	(0.7678)	(0.0470)	(-0.6540)
United States	-4.6604	0.0406	0.4613	0.0101	3.2328	-0.0680
	(-1.1626)	(0.9397)	(0.0753)	(0.5814)	(1.3785)	(-1.2479)

The table shows the results corresponding to the estimation of the model included in equation (3) for each of the countries and subperiods under study: $CSAD_{j,t} = \beta_0 + \beta_1 \left|R_{m,j,t}\right| + \beta_2 R^2_{m,j,t} + \beta_3 CSAD_{RUS,t} + \varepsilon_t$. For reasons of space, only the value of the coefficients β_2 and β_3 are shown, as they are the ones that capture the presence of imitative behavior and the influence of the Russian market. The values in parentheses correspond to the t-statistics. *** indicates that the coefficient is significant at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 1% level.

Table 6. *Estimates of herding incorporating Russia's CSAD. MSCI Emerging.*

	Pre-war		*War*		*Extended war*	
	$R^2_{m,j}$	$CSAD_{RUS}$	$R^2_{m,j}$	$CSAD_{RUS}$	$R^2_{m,j}$	$CSAD_{RUS}$
Czech Republic	3.7478	-0.0408	-13.5077*	-0.0540	11.9470	-0.0332
	(0.7601)	(-0.5911)	(-2.0313)	(-0.6255)	(1.0937)	(-0.3629)
Greece	-4.6140	-0.1060***	1.4750	0.0077	-4.7500	0.0414
	(-1.3270)	(-3.0374)	(1.6231)	(0.5479)	(-1.3830)	(1.0990)
Hungary	-11.5719**	0.0487	-3.0973*	-0.0033	5.4297	0.1061
	(-1.9888)	(1.0343)	(-1.7444)	(-0.1473)	(0.4546)	(1.2684)
Poland	-2.2221	-0.0200	-3.4348**	0.0357	-1.1004	0.0511
	(-1.4509)	(-0.7807)	(-2.3420)	(1.1282)	(-0.1275)	(1.2971)
Turkey	-3.0684***	-0.0657	-3.1248***	-0.0048	-1.1324	-0.0204
	(-3.7338)	(-1.3868)	(-8.3954)	(-0.3350)	(-2.5454)	(-0.3265)
Kuwait	-15.6429**	-0.1386***	-36.1824	-0.0216	-6.6599	-0.0652
	(-2.5518)	(-2.7933)	(-0.4318)	(-0.7415)	(-1.9397)	(-1.0534)
Qatar	-1.1965	-0.0004	-45.0849**	-0.0125	3.0526	-0.0593
	(-0.1504)	(-0.0115)	(-2.2912)	(-0.4769)	(1.6352)	(-1.4959)
Saudi Arabia	1.6990**	-0.0988***	-7.3458*	-0.0165	0.9218	0.0047
	(2.0967)	(-4.6405)	(-1.7259)	(-1.6304)	(0.3775)	(0.1760)
UAE	-10.6314*	0.0851	-39.7740***	-0.0474	-3.0165	-0.0152
	(-1.6813)	(1.1246)	(-3.9511)	(-1.4002)	(-1.0709)	(-0.2278)
Egypt	5.0073**	-0.0543	-0.8016	-0.1053***	4.3450	-0.0922*
	(2.5072)	(-1.0200)	(-0.6684)	(-3.8133)	(3.5927)	(-1.6746)
South Africa	4.6463	0.0532	5.4143	0.0464	16.8558	0.0810*
	(0.8722)	(0.9864)	(0.2688)	(1.6963)	(1.2865)	(1.7098)
China	0.5959	-0.0062	-1.0698	-0.0763***	-1.7247	-0.0834**
	(0.2560)	(-0.1670)	(-0.7410)	(-3.6564)	(-1.2297)	(-2.2803)
India	-3.2008	-0.0097	-8.2959	0.0096	1.7342	-0.0368
	(-0.7455)	(-0.3300)	(-0.4161)	(0.6159)	(0.5605)	(-1.2794)
Indonesia	2.1057	-0.0928***	54.3522	-0.0237	-3.6119	-0.0129
	(0.2873)	(-3.5573)	(1.1050)	(-1.0526)	(-0.8305)	(-0.4502)
Korea	0.3104	-0.0395	5.3307	-0.0002	1.6606	0.0275
	(0.2700)	(-1.6438)	(1.0955)	(-0.0209)	(1.6331)	(0.6324)
Malaysia	1.8052	-0.0369	8.7191	0.0305	3.4610	-0.0168
	(0.3803)	(-1.4619)	(0.4772)	(1.2152)	(0.8810)	(-0.5584)
Philippines	2.6131*	-0.0176	3.0874	0.0082	7.5638	-0.0427
	(1.6835)	(-0.7372)	(0.1278)	(0.3172)	(0.8333)	(-0.9003)
Taiwan	-1.4674	-0.1433***	3.5019	-0.0391***	4.3786***	-0.0794***
	(-1.1102)	(-5.6577)	(0.8674)	(-3.7050)	(4.5222)	(-3.3225)
Thailand	2.4900	-0.0871***	11.9365*	-0.0005	5.9136***	0.0259
	(1.4524)	(-2.8294)	(1.8772)	(-0.0480)	(3.8985)	(0.9364)
Brazil	0.3577	0.0499*	5.5482	0.0221	10.1002***	-0.0186
	(0.1474)	(1.8932)	(0.8420)	(1.0147)	(2.8978)	(-0.3601)
Chile	-1.0175	0.0601	32.3417*	0.0151	-5.1549	0.0503
	(-1.2803)	(1.5423)	(1.9284)	(0.8238)	(-1.6082)	(1.0888)
Colombia	-8.7501***	-0.0066	82.3982	0.0019	-8.4745	0.0679
	(-3.4121)	(-0.1397)	(1.9198)*	(0.0574)	(-1.2686)	(0.7317)
Mexico	6.9888	0.0288	26.6039	-0.0315**	10.8380	0.0060
	(0.8784)	(1.1366)	(0.9272)	(-2.5138)	(1.1699)	(0.1372)
Peru	-3.9256**	-0.0662	-7.1401	-0.0256	-19.1819*	-0.1056
	(-2.3580)	(-1.0265)	(-1.6477)	(-0.7655)	(-1.6985)	(-1.4475)

The table shows the results corresponding to the estimation of the model included in equation (3) for each of the countries and subperiods under study: $CSAD_{j,t} = \beta_0 + \beta_1 \left|R_{m,j,t}\right| + \beta_2 R^2_{m,j,t} + \beta_3 CSAD_{RUS,t} + \varepsilon_t$. For reasons of space, only the value of the coefficients β_2 and $\beta_3$are shown, as they are the ones that capture the presence of imitative behavior and the influence of the Russian market. The values in parentheses correspond to the t-statistics. *** indicates that the coefficient is significant at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 1% level.